The Importance of Director External and Internal Social Networks to Stock Price Crash Risk

Abstract: Prior research documents that information transmitted via director networks affects firms' policies and real economic activities. We explore whether information flow through director networks influences managers' ability to hoard bad news. We find that the extent of external connections of the board of directors is negatively associated with future stock price crash risk. Additional analysis implies that this evidence is driven by firms with more powerful executives, with weaker auditor monitoring, or subject to strong investor protection, and by directors with greater monitoring incentives or responsibilities, with less firm-specific knowledge, and with more valuable reputations to protect. We further find that director external network size is negatively associated with a variety of bad new hoarding signals. Collectively, our research lends empirical support for the monitoring view under which better informed directors narrow the scope for bad news hoarding evident in stock price crash risk. In another series of tests, we fail to find evidence consistent with the information leakage view under which directors pass sensitive firm-specific information to connections who trade on the information before its public release. Other analysis helps dispel the concern that the endogenous match between directors and companies is spuriously responsible for our core results. In contrast to our strong, robust evidence on the role that director external networks play, we only find some results implying that CEO-director internal networks shape stock price crash risk.

1. Introduction

We extend prior research on the determinants of stock price crash risk to include director external and internal social networks.[1] Among different interpretations of stock price crash, bad news hoarding proposed by Jin and Myers (2006) has emerged as the theoretical underpinning of most empirical studies. This theory holds that compensation, reputation, and career concerns motivate the manager to withhold current bad news in hopes of camouflaging it with future good news. A core assumption underlying the bad news hoarding perspective is that the manager has at least partial control over the release of firm-specific bad news. Although extensive prior research is grounded in this theory, little is known on whether information from alternate sources could undermine the manager's control over bad news and attenuate stock price crash risk.

We examine the role that director social networks play in shaping crash risk. We focus on board directors given their responsibility for alleviating agency conflicts stemming from managers' informational advantage by ensuring more transparent disclosures (Armstrong, Guay, and Weber 2010). Director social networks encompass both external and internal connections. We specify director external networks as the aggregate social ties between directors of the firm and executives, officers, and directors of other firms, and internal networks as a common education background shared between directors and the CEO of the firm.[2] Director social networks may affect crash risk in several ways. First, information flowing from external social networks to directors supplements the existing information set of directors, who can leverage

[1] As an important determinant of asset pricing, stock price crash risk explains a significant portion of the market-level equity premium (Gabaix 2012), and affects variation in firm-level cross-sectional expected returns and option prices (Yan 2011; Conrad, Dittmar, and Ghysels 2013).

[2] We focus on CEO-director education ties because social networks formed through a common education background forge strong bonds with enduring impacts since people self-selecting into the same education institution are more alike (e.g., communication is easier among more homophilous people), and shared educational experiences may engender some common beliefs (Cohen, Frazzini, and Malloy 2008; 2010; Shue 2013). Additionally, alumni events provide an opportunity for these people to interact, potentially reinforcing their social connections (He, Pittman, Rui, and Wu 2017).

such information to enforce timelier disclosure of bad news in their monitoring role (Fama 1980; Fama and Jensen 1983). Social networks facilitate information transfer by improving the quality and flow of information, particularly for actors with better connections (Haythornthwaite 1996; Jackson, Rogersy, and Zenou 2016). Consistent with this informational role, prior research finds that information exchange through networks of corporate decision-makers affects real economic activities.[3] Given that stock price crash risk stems from the manager's bad news hoarding that impedes information transfer through formal channels (Jin and Myers 2006), information compiled by directors through alternate informal channels, including social networks, could alleviate the manager's monopoly over information and deter bad news hoarding. Consequently, we expect a lower stock price crash risk for firms with better connected directors. We label this mechanism as the monitoring view of the network-crash risk link.

Second, prior research implies that information could also flow from directors to connections in their external social networks (Cohen et al. 2008; Akbas, Meschke, and Wintoki 2016). It is plausible that directors may deliberately or inadvertently transmit sensitive bad news about the firm to their connections in external networks who subsequently trade on it (Akbas et al. 2016), or profit from the information themselves through insider trading (Cao, Dhaliwal, Li, and Yang 2015). Such informed trading accelerates the impounding of bad news into stock prices and dampens market reactions to the public announcement. As such information flow disseminates the bad news through leakage from directors to social networks, we term this mechanism as the information leakage view of the network-crash risk link. Although both perspectives predict a negative association between director networks and stock price crash risk,

[3] For example, a firm's external social networks affects its operating, investing, and financing policies (Shue 2013; Fracassi 2017), the investment returns of mutual fund managers and informed traders (Cohen et al. 2008; Akbas et al. 2016), analyst recommendations (Cohen et al. 2010), and merger and acquisition outcomes (Ishii and Xuan 2014).

timelier disclosures under the monitoring view generate greater benefits to average investors than the informed trading under the information leakage view.

Third, director internal connections with the CEO stemming from a common education background could affect the information that the CEO shares with directors and, in turn, stock price risk. Since social networks foster interpersonal relations by promoting trust, bonding, allegiance, and the norm of reciprocity (Buskens 2002; Granovetter 2005), the CEO may supply higher quality firm-specific information to connected directors, facilitating tougher monitoring. However, mutual obligations and caring shared by network actors (Silver 1990), as well as the dynamic of punishments and rewards in repeated interactions among network actors (Buskens 2002), could impede a director from strictly disciplining a socially tied CEO against hoarding bad news. Supporting this bonding role, prior research finds that social ties between the CEO and board members undermine the monitoring function of the board.[4]

However, injecting additional tension into our analysis, managers' incentives and ability to withhold bad news may be insensitive to director connections for several reasons. First, directors may conclude that information coming from informal channels such as networks is unreliable or irrelevant. Second, given that it is difficult to verify the exact information set of directors collected through informal social networks, failing to act upon such information may not directly increase directors' legal liability, particularly when the information is potentially noisy. Third, if well-connected directors over-extend themselves by serving on multiple boards,

[4] Prior studies document that CEO-director social ties typically have negative consequences, including less effective monitoring by the board and audit committee (Hwang and Kim 2009; Fracassi and Tate 2012; Coles, Daniel, and Naveen 2014; Bruynseels and Cardinaels 2014), lower financial reporting quality (Krishnan, Raman, Yang, and Yu 2011; Bruynseels and Cardinaels 2014), and a greater incidence of corporate fraud (Khanna, Kim, and Lu 2015).

their busyness may undermine their monitoring performance (Falato, Kadyrzhanova, and Lel 2014). Accordingly, the link between director social networks and crash risk remains unclear.

Examining 28,531 firm-year observations spanning 2000-2015, we find a strong, robust negative association between director external network size and future stock price crash risk. Reflecting its first-order economic importance, as director external network size rises from the 25th to 75th percentile, future stock price crash risk falls, on average, by 26.85% of the sample mean. This result holds when we control for a comprehensive set of crash risk determinants, or match firms based on the extent of bad news to help dispel the concern that our results reflect the lack of bad news, rather than the timelier release of bad news, by well-connected firms.

Next, we deepen our analysis by relying on cross-sectional variation to help distinguish between the competing explanations. If the monitoring view prevails, then we would expect results to be concentrated in the presence of stronger incentives or greater demand for monitoring. Alternatively, if the information leakage view dominates, then the impact should be more pronounced in the presence of greater opportunities for informed trading. At the firm level, we find that the results are concentrated in firms with more powerful CEOs, firms with CEOs who are more capable of bad news hoarding, firms with weaker alternative monitoring by the auditor, and firms subject to stronger shareholder rights protection. At the director level, we find that the results are mainly driven by independent directors who have stronger incentives to monitor, by audit committee members who have greater responsibility to monitor, by directors who will suffer greater reputational loss from a monitoring failure, and by directors lacking firm-specific knowledge who benefit more from information transferred through networks.

To further explore the mechanisms at work, we also directly test whether director social networks affect timelier bad news disclosure. We find that director external social networks are negatively associated with multiple bad-news-hoarding channels or signals, including opaqueness, discretionary accruals (both positive and negative), the incidence of meeting or beating analyst forecasts via accrual manipulation, real earnings management, and the short interest ratio. These results reconcile with the interpretation that better informed directors constrain the bad news hoarding that is behind stock price crashes. Using multiple measures of informed trading, including the short interest ratio, option trading volume to stock trading volume ratio, PIN score, inside trading, and institutional ownership, we fail to find that our main results vary with informed trading. Collectively, our analysis lends support to the monitoring, rather than the information leakage view. In shifting gears to focus on internal connections, we also find a negative, albeit weaker, relation between CEO-director education ties and crash risk.

Although director networks—which are routinely formed in the fairly distant past—are exogenous to future crash risk, the hiring of a director with an expansive network could be an endogenous firm decision. We conduct two tests to tackle this threat to reliable inference. First, we exploit the relatively exogenous shifts in board composition induced by director retirement. In a difference-in-difference framework, we find that within firms experiencing a director retirement, firms with a larger loss in director connections exhibit a greater increase in crash risk from the pre- to post-retirement year. Second, we directly examine whether directors with better networks refrain from accepting appointments to companies with greater *ex ante* stock price crash risk. We fail to find any evidence supporting this perspective, implying that it is unlikely that the endogenous company-director match is spuriously responsible for our results.

We make several contributions to extant research. First, we gauge the role that alternative information sources play in crash risk. Prior research extensively examines whether crash risk is shaped by financial reporting quality (Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a; Kim and Zhang 2014; DeFond, Huang, Li, and Li 2015; Kim and Zhang 2016; Zhu 2016; Ertugrul, Lei, Qiu, and Wan 2016; Lobo, Wang, Yu, and Zhao 2017), and the manager's incentives and characteristics (Kim, Li, and Zhang 2011b; He 2015; Callen and Fang 2015a; Kim, Wang, and Zhang 2016). However, most studies implicitly assume that the manager controls the release of bad news due to her information monopoly, and that the board critically depends on the manager for firm-specific information (Adams and Ferreira 2007), ignoring the presence of alternative information channels.[5] Our results support the intuition that information shared through social networks complements the existing information set of directors, weakens the information monopoly of the manager, reduces the incentives and ability of the manager to hoard bad news, and attenuates stock price crash risk.

Second, despite the negative consequences of stock price crash for investor welfare and market stability (e.g. Yan 2011), extant research only identifies a few formal control mechanisms that curtail such extreme downside tail risk, including conditional accounting conservatism (Kim and Zhang 2016), effective internal controls over financial reporting (Lobo et al. 2017), and stricter monitoring by auditors (Callen and Fang 2017). Our research has practical implications for firms eager to improve their corporate governance. In evaluating prospective directors, firms could consider the role that director social networks play in preventing bad news hoarding that is behind stock price crashes.

[5] In an exception, Kim, Li, Lu, and Yu (2016) conjecture that investors can infer a firm's performance and potential bad news from analyzing the disclosures of its comparable peers, with this enhanced understanding reducing the manager's incentive and ability to withhold bad news. Consistent with expectations, they report a negative association between the financial statement comparability of a firm and expected crash risk. We complement Kim et al. (2016) in that they focus on an alternative information source via formally disclosed financial statements of peer firms, whereas we concentrate on information transferred through competing informal information channels—social networks. Additionally, our results have different implications from that of Kim et al. (2016). First, in terms of alleviating crash risk, financial statements comparability mainly benefits sophisticated investors who can identify comparable firms and discern managers who likely withhold bad news, whereas director social networks potentially help to enforce the timelier release of bad news that benefits all investors. Second, a firm cannot alter financial statement comparability of its peer firms, but has control over board appointments. As such, our results have more direct implications for the protection of average investors and corporate governance practice.

Third, prior research on information sharing documents certain benefits of director external networks for the advising function of the board, including its impact on firm finance policy (Fracassi 2017), accounting and stock returns (Larcker, So, and Wang 2013), and terms of loan transactions (Engelberg, Gao, and Parsons 2012). In contrast, extant research seldom examines whether director external networks affect the monitoring function—an important question given prior evidence that the two roles compete for directors' time and task focus (Faleye, Hoitash, and Hoitash 2011). Our evidence implies that director external ties also strengthen the monitoring function by constraining bad news hoarding, consistent with the narrative that information acquired through external ties complements both functions (Kim, Mauldin, and Patro 2014). In contrast, information stemming from the manager engenders a trade-off between the two functions (Adams and Ferreira 2007).[6]

Fourth, prior research on CEO-director internal ties mostly focuses on its dark side, including its negative impact on monitoring (Krishnan et al. 2011; Bruynseels and Cardinaels 2014; Khanna et al. 2015) and firm performance (Hwang and Kim 2009; Fracassi and Tate 2012; Coles et al. 2014). We document that such ties also benefit firms by improving information exchange that manifests in lower stock price crash risk.

The rest of the paper proceeds as follows. Section 2 reviews prior theory and evidence in motivating the testable predictions. Section 3 outlines the empirical design and sample construction. Section 4 covers the results, while Section 5 concludes.

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[6] Adams and Ferreira (2007) model the dual role of the board as advisor and monitor of the manager. In their model, the CEO faces a trade-off in sharing firm-specific information with the board. On one hand, better information sharing potentially improves the effectiveness of board advising, enhancing firm value. On the other hand, better informed boards, particular better informed independent boards, also impose tougher monitoring on the manager (Chen, Cheng, and Wang 2015). Consequently, the CEO may be reluctant to share information with independent boards. In contrast, information acquired from director external networks does not involve this trade-off, implying that such information benefits both the advising and monitoring functions.

2. Motivation

2.1. Prior Research on Crash Risk

Jin and Myers (2006) model crash risk from an agency standpoint. They hold that opacity rather than poor investor protection leads to stock price crash. Given their career and compensation concerns, managers have both the incentive and ability to hide bad news stemming from temporary bad performance by at least partially controlling public access to information about firm fundamentals. The increased opacity, in turn, facilitates bad news hoarding. However, in the limit, as accumulated bad news reaches a tipping point, it is suddenly released to the market at once, leading to a large drop in stock price, or a crash. Jin and Myers (2006) report empirical evidence consistent with their prediction.

In primarily relying on the agency perspective proposed in Jin and Myers (2006) to explore the determinants of stock price crash risk, prior empirical research implies that ex post realized stock price crash risk increases with opacity measured with absolute discretionary accruals (Hutton et al. 2009), particularly accruals in more recent years and less reliable accruals associated with operating assets (Zhu 2016). Crash risk rises when the scope for bad news hoarding is greater evident in the presence of complicated tax strategies (Kim et al. 2011a), less readable and more ambiguous annual reports (Ertugrul et al. 2016), real earnings smoothing (Khurana, Pereira, and Zhang 2017), stronger incentives for withholding bad news arising from managerial stock-based compensation (Kim et al. 2011b) or claw back provisions in executive compensation (Bao, Fung, and Su 2017), CEO overconfidence (Kim et al. 2016), or high stock liquidity owing to transient investor sales upon bad news disclosure (Chang, Chen, and Zolotoy 2016).[7]

[7] Other studies attempt to broaden our understanding of stock price crash from the standpoint of market dynamics. Miller (1977) and Hong and Stein (2003) demonstrate that investor opinion divergence leads to the overvaluation of stocks when opinions of bearish investors remain hidden due to short sale constraints.

Since stock price crash increases volatility and uncertainty and erodes investor confidence, it is important to understand the control mechanisms that can curtail such extreme downside tail risk. Prior research identifies several such formal control mechanisms, including more timely recognition of bad news under conditional accounting conservatism that constrains managers' ability to withhold adverse private information (Kim and Zhang 2016), effective internal controls over the financial reporting system (Lobo et al. 2017), the adoption of International Financial Reporting Standards that impose tougher requirements for financial reporting quality (DeFond et al. 2015), and tighter monitoring by external auditors through long-term auditor-client relationships (Callen and Fang 2017).[8]

Given that crash risk critically hinges on the extent to which the manager can conceal adverse information from internal and external monitors and investors, it is crucial to consider whether alternative information sources, such as social networks, weaken the incentive and capacity of the manager to withhold bad news. We help close this gap in extant research.

2.2 Prior Research on Social Networks

Social networks influence economic activities for at least three reasons. First, it affects the flow and quality of information since people tend to have more trust in information coming from personal connections (Granovetter 2005). Second, under the social norm of reciprocity, social

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It is more likely that this accumulated hidden information is divulged during market declines, leading to stock price crashes. Chen, Hong, and Stein (2001) find that stock price crashes are preceded by a large trading volume and high past returns, consistent with investor opinion divergence and stock price bubbles contributing to crashes. Another potential cause for crash risk is default risk, as firms near default more likely release bad news leading to price crash (Zhu 2016). However, prior research fails to find any positive association between crash risk and default risk measured by either financial leverage or bankruptcy risk (Hutton et al. 2009; Zhu 2016).

[8] Besides formal monitoring mechanisms, prior research also explores a variety of informal institutional structures and finds that crash risk subsides with the CEO's aversion to downside risk stemming from their inside debt holdings (He 2015), a firm's financial statement comparability (Kim et al. 2016), levels of religiosity (Callen and Fang 2015a), performance in corporate social responsibility (Kim, Li, and Li 2014), and a firm's proximity to SEC headquarters (Kubick and Lockhart 2016).

networks act as a major source of reward and punishment. Third, repeated interactions among actors in the network foster trust and mutual understanding (Granovetter 2005).

Prior research documents that external ties improve information flow among connected firms and affect their real economic activities. For example, research finds that firms tend to adopt more similar policies if their executives graduate from the same MBA section of Harvard Business School (Shue 2013), or if their executives and directors are connected through current and past employment, education, and other activities (Fracassi 2017), consistent with enhanced information flow among tied firms. Firm directors and officers also transfer information to other important market participants via networks. Such information transfer along the education network prompts better performance by mutual fund managers and financial analysts on stocks of connected firms (Cohen et al. 2008, 2010), and lower interest rates offered by connected banks (Engelberg et al. 2012) as a result of better information flows and monitoring rather than favoritism of connected deals. Cross-firm social connections could also have downsides, including negative acquisition performance when the target is tied to the acquirer firm (Ishii and Xuan 2014), and greater wage premia for better connected CEOs as compensation for their informational advantage (Engelberg, Gao, and Parsons 2013).[9]

Prior research implies that internal ties between the CEO and directors undermines board monitoring and firm performance. Fracassi and Tate (2012) find that powerful CEOs tend to hire directors socially tied to them, and CEO-director ties are associated with lower firm value and more value-destroying acquisitions. Such appointment-based CEO-director ties are also linked to weaker board monitoring (Coles et al. 2014) and higher fraud risk (Khanna et al. 2015). In return, CEOs enjoy excessive compensation and exhibit lesser pay-/turnover-performance

[9] Other research documents network effects on the performance of venture capitalists (e.g., Hochberg, Ljungqvist, and Lu 2007), as well as on investment decisions of individuals (e.g., Hvide and Östberg 2015).

sensitivity when they are socially connected to directors who appear independent by conventional standards (Hwang and Kim 2009; Nguyen 2012).

2.3. Hypotheses Development

2.3.1 Director external networks and crash risk

Social networks operate as an important conduit for information exchange. Network theory suggests that the position of an actor in the network affects the extent of information exchange. Actors with a larger sized network and highly connected actors have greater access to information resources (Haythornthwaite 1996), and are more likely to take on the role of a hub in the network (Jackson et al. 2016). Importantly, hub-like actors are well-positioned to collect and control private information, which they can exploit to their advantage.

Consistent with external networks transmitting value-creating information, prior research finds that external ties improve the advising function of the board (Larcker et al. 2013; Fracassi 2017; Engelberg et al. 2012). Since both advising and monitoring improve when the board is better informed (Adams and Ferreira 2007), and that the two functions are potentially complementary (Kim et al. 2014), we anticipate that information exchanged through external networks also facilitates monitoring by the board.

Depending on the direction of information flow, director external networks could affect crash risk through two mechanisms. Under the monitoring view, information travels from networks to directors, enabling them to better monitor the manager. Specifically, boards with more expansive networks access more comprehensive and timelier information about the current operations and future outlook of the firm, such as the launch of a new product by peer firms that potentially accelerates obsolescence of the firm's existing products, deteriorating financial conditions of major customers, tightening of the lending policy of major capital providers, the pending acquisition of an important supplier, potential strategic alliances among competitors, upcoming regulatory restrictions, loss of major customer contracts, etc. Such knowledge complements the existing information set of directors, ensuring that they are in a better position to evaluate the risks, threats, and uncertainty faced by the firm that, in turn, makes it harder for the manager to conceal bad news. Consequently, managers are more inclined to disclose bad news in the presence of a well-connected and better informed board. In the other direction, information collected from informal social networks will not be useful if it is unreliable or does not pertain to the specific firm. Moreover, to the extent that it is difficult for outsiders to clearly observe the private information directors collected through their networks, failure to act upon such private information by directors may not increase their legal liability.[10] Further, well-connected directors may become over-extended by serving on multiple boards, with their busyness undermining their monitoring role (Falato et al. 2014). Last, well-connected directors who already enjoy strong reputations may relax their managerial monitoring if the cost of intensive oversight no longer justifies any additional benefit (Guedj and Barnea 2009).

Under the information leakage view, material non-public information about the firm flows from directors to firm outsiders through director networks. Despite extensive laws, regulations, and corporate policies prohibiting the release of private information and exploiting such information for trading, leakage could still occur inadvertently through unguarded interactions between a director and connections in networks, or by sophisticated traders piecing together information from multiple sources in their information search (Borgatti and Cross 2017). In examining abnormal trading returns of network connections, prior research implies that

[10] For example, Baum, Larcker, Tayan and Welch (2017: 3) stress that: "Under the business judgment rule, courts have ruled that in the absence of "red flags" outside directors are permitted to rely exclusively on information provided by management, and if they do so, courts will assume a hands-off posture even if the board decision is clearly wrong."

privileged information flows from directors to mutual fund managers, short sellers, option traders, and institutional investors (Cohen et al. 2008; Akbas et al. 2016). In particular, Akbas et al. (2016) find that sophisticated traders better anticipate earnings surprises of highly connected firms, and that a higher fraction of negative news concerning such firms is already impounded in prices before the announcement. If such leakage accelerates the incorporation of bad news into the market, it should alleviate the market surprise when bad news is publicly released.[11] We expect under both the monitoring and information leakage views that crash risk will subside when director external networks are larger, which we formalize in this alternative hypothesis: [12]

> H_1: There is a negative association between the size of director external social networks and stock price crash risk.

Although both views predict a negative association between crash risk and director external network size, the mechanisms at work as well as implications for investors are fundamentally different. Under the monitoring view, bad news is disclosed through formal voluntary and mandatory disclosure channels on a timely basis. Such disclosure alerts all investors and strengthens corporate governance and investor protection. Under the information leakage view, bad news travels discreetly within exclusive networks and the trading on such news enriches only the small group of connected investors and corporate insiders.

2.3.2 Director internal networks and crash risk

School ties constitute an important type of social network with broad scope and long-lasting effects. CEO-director education ties potentially generate opposing effects on crash risk.

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[11] In contrast to trades executed by market-wide investors on the public release of bad news, trades by a small group of connections more likely lead to a gradual correction of stock prices, rather than a crash.

[12] We develop hypotheses within the framework of bad news hoarding proposed by Jin and Myers (2006). We recognize that under either the monitoring or information leakage view, more expansive board network may not reduce crash risk if the latter is caused by investor opinion divergence (Hong and Stein 2003), information blockage (Cao, Coval, and Hirshleifer 2002), or other features of market dynamics such as stock liquidity (Chang et al. 2016).

First, the homophily principle central to social network theory suggests that people feel more comfortable when seeking friendship and interacting with those who are similar to themselves, and interactions occur more frequently among similar people than among dissimilar people (McPherson, Smith-Lovin, and Cook 2001). Shared education experience nurtures a common way of thinking and problem solving, engenders bonding and proximity, promotes close interaction and support, and fosters trust and information sharing according to social network theory (Granovetter 1985, 2005; Buskens 2002). Although managers are naturally eager to share good news with all board members to showcase their performance and increase bargaining power, they have particularly strong incentives to withhold bad news out of compensation and career concerns (Kothari, Shu, and Wysocki 2009). The sense of kinship and trust makes the CEO more inclined to interact with connected directors and openly share with them sensitive private information, particularly bad news (Cao, Dhaliwal, Li, and Yang 2015). Equipped with such privileged information, connected directors are in a better position to constrain bad news hoarding.

However, the behavior of actors sharing a social network is governed by communal norms which promote mutual caring and trust (Silver 1990). In undertaking monitoring, a director may be concerned about the CEO's welfare when their business relationship is inextricably mixed with their social links (Granovetter 2005). Importantly, trust is dynamic and evolves with repeated interactions. In a repeated trust game, actors are sanctioned for untrustworthy behavior, and rewarded with greater trust for trustworthy behavior (Buskens 2002). The social norm of reciprocity and concerns for subsequent consequences could impede a director from effectively disciplining the manager with personal ties. Additionally, given that the CEO may be inclined to appoint directors with personal ties (Fracassi and Tate 2012), the endogenous selection of tied directors may enhance CEO power and weaken board monitoring (Hermalin and Weisbach 1998). Prior research generally finds that CEO-director social ties undermine board monitoring.[13]

Under the information leakage view, insider trading by connected directors on private bad news accelerates the incorporation of bad news into the market. In support of this intuition, Cao et al. (2015) report that connected directors earn higher returns from open-market sales, but not from open-market purchases, than unconnected directors. Further, the net sales of connected directors predict future bad news for up to three quarters, suggesting insider trading of connected directors may preempt future public announcement of bad news.

In summary, we expect an ambiguous relationship between CEO-director ties and bad news hoarding under the monitoring view, but anticipate a negative relationship under the information leakage view. Consequently, we formalize the following null hypothesis:

H_2: There is no association between CEO-director social ties and stock price crash risk.

3. Sample, Variable Measurement and Descriptive Statistics

3.1. Data Sources and Sample

Our sample period starts in 2000, the earliest year with data available in BoardEx for director networks, and ends in 2015, the latest year with complete data to measure one-year-ahead variables. In addition, we collect: 1) stock return data from the Centre for Research in Security Prices (CRSP); 2) accounting data from COMPUSTAT annual files; 3) analyst information from I/B/E/S; 4) institutional ownership data from Thompson-Reuters Institutional Holdings Database; and 5) audit-related data from Audit Analytics. We exclude observations with non-positive total assets and equity book values, observations with year-end share prices less than

[13] In particular, prior research finds CEO-director social links are associated with a lower likelihood of directors dissenting on proposals initiated by management or large shareholders (Wei, Hualin, and Shan 2016).

one dollar, and observations with fewer than six months of stock return data. Our final sample consists of 28,531 firm-year observations for the years 2000 to 2015 inclusive.

3.2. Measure of Director Social Networks

We measure director social networks using two metrics based on director's external and internal connections. We follow Akbas et al. (2016) in specifying our external-connection measure, which reflects a variety of links through schools attended, current and previous employers, military service and civic activities. More specifically, we first aggregate at the board level each director's social connections with officers and directors of other firms obtained from BoardEx, and then regress the natural logarithm of board-level total external connections on the natural logarithms of firm size, board size, firm age, number of analysts, and institutional ownership. We rely on the residual values from the cross-sectional regressions to proxy for board-level director external social networks (*CONNECTEDNESS*). This approach helps ensure that our measure of director networks is not driven by potentially correlated firm characteristics, and helps attenuate potential coefficient bias on *CONNECTEDNESS* arising from any omitted variables correlated with these firm attributes. The second measure is an internal-connection through school ties (Cohen et al. 2008, 2010), specified as the natural logarithm of the total number of board members' connections with the CEO through prior education (*BOARD_CEO_TIE*).

3.3. Measures of Firm-Specific Crash Risk

Firm-specific daily returns are a critical input into calculating various metrics of firm-specific stock price crash risk. We follow Jin and Myers (2006) in estimating firm-specific daily returns from this expanded market and industry index model regression for each firm and year:

$$r_{jt} = \alpha_j + \beta_{1j} r_{m(t-1)} + \beta_{2j} r_{i(t-1)} + \beta_{3j} r_{mt} + \beta_{4j} r_{it} + \beta_{5j} r_{m(t+1)} + \beta_{6j} r_{i(t+1)} + \varepsilon_{jt}\ , \tag{1}$$

where r_{jt} is the raw value of return on stock *j* in day *t*, r_{mt} is the return on the CRSP value-weighted market index on day *t*, and r_{it} is the return on the value-weighted industry (i.e., the two-digit SIC code) index. To account for non-synchronous trading, we include lead and lag terms for the value-weighted market and industry indices in the regression (Dimson 1979). The firm-specific daily return, R_{jt}, is defined as the natural log of one plus the residual return from Equation (1). We log transform the raw residual returns to reduce the positive skew in the return distribution and help ensure symmetry (Chen et al. 2001).[14]

After extensive prior research (e.g., Chen et al. 2001; Jin and Myers 2006; Hutton et al. 2009; Callen and Fang 2015a), we calculate three measures of (*ex post*) firm-specific crash risk for each firm-year observation. Our first measure is the negative coefficient of skewness (*NCSKEW*), i.e., the negative of the third moment of each stock's firm-specific daily returns (R_{jt}) divided by the cubed standard deviation. Thus, for any stock *j* over the fiscal year *T*,

$$NCSKEW_{jT} = -\left(n(n-1)^{3/2}\sum R_{jt}^{3}\right)\Big/\left((n-1)(n-2)(\sum R_{jt}^{2})^{3/2}\right), \tag{2}$$

where *n* is the number of observations for stock *j* during the fiscal year *T*. The denominator is a normalization factor (Greene 1993).

Our second measure is the down-to-up volatility of firm-specific daily returns (*DUVOL*) calculated as follows:

$$DUVOL_{jT} = \log\left\{(n_u - 1)\sum_{DOWN} R_{jt}^{2} \Big/ (n_d - 1)\sum_{UP} R_{jt}^{2}\right\}, \tag{3}$$

where n_u and n_d are the number of up and down days over the fiscal year *T*, respectively. For any stock *j* over a one-year period, we denote days with firm-specific daily returns above (below) the mean of the period as the "up" ("down") sample. We further compute the standard deviation for each sample separately. *DUVOL* is the log ratio of the standard deviation of the "down" sample to the standard deviation of the "up" sample.

[14] Our results (untabulated) remain robust if we measure firm-specific crash risk based on raw residual returns.

Our third measure is the number of days with negative extreme firm-specific daily returns minus the number of days with positive extreme firm-specific daily returns (*COUNT*). A firm-specific daily return is treated as a negative (positive) extreme return if it exceeds 3.09 standard deviations below (above) the mean firm-specific daily return over the fiscal year, with 3.09 selected as a cut-off to yield frequencies of 0.1 percent in the normal distribution (Hutton et al. 2009). In our empirical tests, we employ one-year-ahead *NCSKEW* ($NCSKEW_{T+1}$), *DUVOL* ($DUVOL_{T+1}$), and *COUNT* ($COUNT_{T+1}$) as the dependent variables. [15]

3.4. Research Design and Control Variables

To test the predictions in H1 and H2, we estimate the following regression:

$$CRASHRISK_{j,T+1} = \alpha_0 + \alpha_1 CONNECTEDNESS_{j,T} + \alpha_2 BOARD\_CEO\_TIE_{j,T} + \sum_k \alpha_k Controls_{j,T}^{k} + YearDummies + IndustryDummies + \varepsilon_{j,T+1}, \quad (4)$$

where $CRASHRISK_{T+1}$ is measured by $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $COUNT_{T+1}$ in successive estimations. All regressions control for year and industry fixed-effects. We estimate the models using pooled Ordinary Least Squares with White standard errors corrected for firm clustering. We focus on the role that *CONNECTEDNESS* and *BOARD_CEO_TIE* play in future crash risk.[16]

We follow prior research by controlling for these variables in the regressions (Chen et al. 2001; Jin and Myers 2006): $NCSKEW_T$, defined as the negative coefficient of skewness for firm-specific daily returns in fiscal year *T*; KUR_T, defined as the kurtosis of firm-specific weekly returns in fiscal year *T*; $SIGMA_T$, defined as the standard deviation of firm-specific weekly returns in fiscal year *T*; RET_T, defined as the cumulative firm-specific weekly returns in fiscal year *T*; MB_T, defined as the market-to-book ratio at the end of fiscal year *T*; LEV_T, defined as the book value of all

[15] Higher values of *NCSKEW*, *DUVOL* and *COUNT* imply higher crash risk.

[16] To address potential outliers and data coding errors, we winsorize all continuous variables at 1st and 99th percentiles except for the dependent variables, consistent with Jin and Myers (2006) and Hutton et al. (2009). Our core evidence is nearly identical without winsorizing.

liabilities divided by the total assets at the end of fiscal year *T*; $LNSIZE_T$, defined as the log of market value of equity at the end of fiscal year *T*; ROA_T, defined as the operating earnings divided by the book value of total assets at the end of fiscal year *T*; and $DTURN_T$, defined as the average monthly share turnover over fiscal year *T* minus the average monthly share turnover over the year *T-1*, where monthly share turnover is calculated as the monthly share trading volume divided by the number of shares outstanding over the month.

Consistent with Hutton et al. (2009), we include financial reporting opacity ($OPAQUE_T$), computed as the annual performance-adjusted discretionary accruals (Kothari, Leone, and Wasley 2005).[17] To control for real earnings management, we include abnormal production costs (ABN_PROD_T), abnormal discretionary expense (ABN_DISEXP_T), and abnormal cash flow from operations (ABN_CFO_T) (Francis, Hasan, and Li 2016). We also control for the presence of dividend payments (DIV_T) (Kim, Luo, and Xie 2016), auditor tenure ($TENURE_T$), firm age (AGE_T) (Callen and Fang 2017), Big Four auditor ($BIGN_T$) and industry specialist ($SPEC_T$) auditor status (Lim and Tan 2008; Reichelt and Wang 2010). We control for analyst coverage (ANA_T) since Chen et al. (2001) find that firms with greater analyst coverage suffer more crashes in the future. We follow Callen and Fang (2013, 2015b) by controlling for the short interest ratio (SIR_T) and institutional ownership ($INST_T$). Finally, we include the strength of SEC monitoring ($DISTANCE_T$), which equals to one if the distance between a firm's headquarters and the closest SEC regional or national office is within 100 kilometers, and zero otherwise (Kedia and Rajgopal 2011). In Appendix A, we summarize the variable specifications.

3.5. Descriptive Statistics

[17] We also use a modified Dechow and Dichev's (2002) accrual quality measure in Francis, LaFond, Olsson, and Schipper (2005) to measure firm-level reporting quality, and the results (untabulated) remain robust.

In Table 1, we present in Panel A descriptive statistics for key variables used in our regressions. The mean values of future stock price crash risk measures $NCSKEW_{T+1}$, $DUVOL_{T+1,}$ and $COUNT_{T+1}$ are -0.0794, -0.1194, and -0.3229, respectively. The mean value and standard deviation of $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ are similar to those reported in prior work (e.g., Chen et al. 2001; Callen and Fang 2015a, 2015b). The mean value and standard deviation of *CONNECTEDNESS* are 0.0015 and 0.6015, respectively, comparable to the corresponding statistics of 0.0011 and 0.5192 reported in Akbas et al. (2016).

Panel B provides a Pearson correlation matrix for the key variables under study. Our future stock price crash risk measures, $NCSKEW_{T+1}$, $DUVOL_{T+1}$, and $COUNT_{T+1,}$ are predictably all significantly and positively correlated with each other. Importantly, *CONNECTEDNESS* is significantly negatively correlated with all three of the future crash risk measures at the 1% level (two-tailed), consistent with H1 regarding a negative association between director external social networks and crash risk. The correlation coefficients between *BOARD_CEO_TIE* and all three future crash risk measures are significant and positive, providing no preliminary support for H2 that there is no association between CEO-director social ties and crash risk. Reinforcing prior research, all crash risk measures are significantly correlated with a number of firm-level variables.

4. Empirical Tests

4.1. Main Results and Sensitivity Analysis

In Table 2, to gauge the role of director external networks and director-CEO ties, we report the results where we include both *CONNECTEDNESS* and *BOARD_CEO_TIE* in the same regressions. Across all three specifications of future stock price crash risk, the coefficients on *CONNECTEDNESS* are negative and significant at the 1% level (*t*-statistics= -3.08, -3.99, and -3.01, respectively). In contrast, the results on *BOARD_CEO_TIE* are much weaker with its coefficients negative and significant at the 10% and 5% levels in only two out of the three specifications (*t*-

statistics= -1.52, -1.74 and -2.53, respectively). To calibrate economic importance, we follow prior research by comparing the crash risk when *CONNECTEDNESS* and *BOARD_CEO_TIE* are set at the 25th and 75th percentile of the sample. On average, the decreases in stock price crash risk corresponding to this interquartile shift is 26.85 percent of the sample mean across the three alternative measures of crash risk for *CONNECTEDNESS*, and is 14.88 percentage of the sample mean across the two alternative measures of crash risk for *BOARD_CEO_TIE*.[18,19]

The estimated coefficients on the control variables are generally highly significant in the predicted directions across all three crash risk models. Specifically, consistent with Chen et al. (2001) that growth stocks, stocks with high trading volume, stocks of large firms, and stocks with greater analyst coverage are more likely to crash, *MB*, *DTURN*, *LNSIZE*, and *ANA* load significantly positive. We observe significantly negative coefficients on *LEV* and positive coefficients on *OPAQUE*, in line with Hutton et al.'s (2009) results suggesting that tighter lender monitoring of highly leveraged firms constrains managerial bad news hoarding and that opaque firms are more likely to crash. In addition, the coefficients on *ABN_PROD* and *ABN_DISEXP* are significantly positive, reinforcing Francis, Hasan and Li's (2016) evidence that firms orchestrating real earnings management are more prone to crash. Reconciling with the learning-by-monitoring perspective of auditor-client relationships in Callen and Fang (2017), *TENURE* enters negatively. Finally, similar to Callen and Fang (2013) and Kubick and Lockhart (2016), the coefficients on *INST* and *DISTANCE* load in the predicted directions across all three columns.

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[18] The specific percentage changes for one-year-ahead *NCSKEW*, *DUVOL*, and *COUNT* are 50.30 percent, 17.88 percent, and 12.37 percent, respectively, as *CONNECTEDNESS* rises across the interquartile range. The specific percentage changes for one-year-ahead *DUVOL* and *COUNT* are 12.71 percent and 17.04 percent, respectively, as *BOARD_CEO_TIE* increases across the interquartile range.

[19] Since independent directors are likely to focus more intently on monitoring that disciplines firms against bad news hoarding, we re-estimate the regressions in Table 2 after replacing external networks of all directors (*CONNECTEDNESS*) with that of independent directors (*CONNECTEDNESS_IndepD*). In untabulated results, we find that across all three regressions, the coefficients for both *CONNECTEDNESS_IndepD* and *BOARD_CEO_TIE* are consistently negative and significant.

In short, the findings in Table 2 uniformly support the narrative that the extent of aggregate director external networks is associated with lower future stock price crash risk. We also provide evidence implying that director-CEO connections constrain crash risk, although the results are considerably weaker and sensitive to the crash risk measure under study.

In Table 3, we report evidence from examining whether our core results are materially sensitive to analyzing a different measure of external connections, adding control variables to the regressions, and evaluating competing explanations. In Panel A, we measure stock price crash risk with $NCSKEW_{T+1}$. First, although *CONNECTEDNESS* as constructed in Akbas et al. (2016) is orthogonal to the five firm attributes, it may admit measurement error of unknown severity. For example, even when the extent of a firm's board external connections remains stable, *CONNECTEDNESS* will vary with changes in firm attributes. To alleviate this issue, we re-specify *CONNECTEDNESS* as the raw value of board external connections in Column (1). Second, disclosures of comparable firms is another alternate information source, as investors can infer a firm's potential bad news from disclosures of its comparable peers (Kim et al. 2016). In Column (2), we control for the firm-year measure of financial statement comparability in De Franco, Kothari, and Verdi (2011).[20] Third, prior studies suggest that financial reporting opacity has a first-order impact on stock price crash risk (Hutton et al. 2009; Kim and Zhang 2014; Zhu 2016). In Column (3) and (4), we supplement our measure of opacity (*OPAQUE*) with accrual quality (Dichev and Dechow 2002) and F-score (Dechow, Ge, Larson and Sloan 2011), respectively. Prior research implies that undertaking complex tax strategies exacerbates opacity, leading to greater crash risk (e.g., Kim et al. 2011a). In Columns (5), we control for corporate tax avoidance with the cash effective tax rate. In these regressions, we find that *CONNECTEDNESS* continues to load

20 We thank Professor Verdi for providing the financial statement comparability score at http://mitmgmtfaculty. mit.edu/rverdi/.

negatively at the 5% level or better despite the major sample attrition in some estimations. In contrast, we only find some supportive evidence for *BOARD_CEO_TIE*.

Last, board connections affect firm policy (Shue 2013; Fracassi 2017). The superior advisory function performed by well-connected directors may translate into better performance, which, in turns, lowers the incidence of bad news. It follows that our main results could reflect the absence of bad news, rather than the timelier release of bad news by well-connected firms. To confront this competing explanation, we measure the extent of bad news released to the market with one-year-ahead stock returns, assuming that observations with future stock returns in the bottom tercile of the full sample (low-return subsample) release more bad news than observations in the top tercile (high-return subsample). This partition allows us to match observations based on the extent of bad news. If the main results are due to the accelerated release of bad news by well-connected firms, *CONNECTEDNESS* should load negatively mainly for the low-return subsample where bad news is more concentrated, but not for the high-return subsample where bad news is more sparse. Supporting this intuition, we find that *CONNECTEDNESS* enters negatively at the 1% level for the low-return subsample in Columns (6), and fails to load for the high-return subsample in Column (7). Moreover, we directly examine whether board connections are associated with the extent of bad news release by substituting future stock returns for crash risk as the dependent variable. If firms with better connected boards release less bad news, then we would expect to observe a positive relation between *CONNECTEDNESS* and future stock returns. In untabulated results, we find that *CONNECTEDNESS* has no perceptible impact on future stock returns (*t*-statistic=-0.46). Collectively, our evidence is consistent with well-connected firms hoarding less bad news, rather than having less bad news in the first place. In Panels B and C, we find very similar results when we measure stock price crash risk with $DUVOL_{T+1}$ and $COUNT_{T+1}$, respectively.

4.2. Cross-sectional Analyses – Monitoring Explanation

In this section, we deepen our analysis by striving to identify the factors that prompt cross-sectional differences in the economic consequences of director networks to investors. Our predictions on the links between director networks and future firm-specific crash risk are grounded conceptually in: (i) agency conflicts between managers and shareholders engendering managerial bad-news-hoarding; and (ii) directors remaining eager to detect and deter this behavior. Accordingly, we examine whether the impact of director networks on future crash risk hinges on both the severity of agency conflicts and the degree of directors' monitoring incentives, evident in CEO characteristics; external monitoring by professional auditors; the protection of shareholders' rights; and director characteristics. To provide direct evidence on the underlying mechanism, we also analyze whether director networks are associated with various channels and signals of bad news hoarding.

4.2.1 CEO Characteristics

Managerial agency conflicts arising from the separation between ownership and control in U.S. firms (Jensen and Meckling 1976) motivates examining whether the relation between director networks and future crash risk becomes stronger when firms experience worse agency conflicts stemming from CEO power and CEO ability.

Prior research implies that director networks will have a larger impact on constraining crash risk when CEO power is high. Adams and Ferreira (2007) and Harris and Raviv (2008) suggest that managers are reluctant to share information with directors since they may use such information to tighten their monitoring of managers. Similarly, Lisic, Neal, Zhang and Zhang (2016) argue that a powerful CEO is more apt to provide the board with low-quality information or less information, which undermines the monitoring process. Friedman (2014) develops an agency model holding that a powerful CEO can extract rents by manipulating financial reporting to exaggerate firm performance. Abernethy, Kuang and Qin (2015) document that powerful CEOs exploit their influence over corporate policy in pursuing private benefits. It follows that a more powerful CEO will be more likely to engage in bad-news-hoarding activities and, in turn, directors will be more likely to rely on the knowledge obtained from their own networks in helping identify and deter managers from suppressing bad news in this situation.

A similar rationale applies to CEO ability. Recent evidence implies that managerial ability is a major determinant of firm-level manipulation. Koester, Shevlin, and Wangerin (2016) and Habib and Hasan (2014) find that firms with superior managerial ability exhibit more tax avoidance and more severe empire building in the form of overinvestment, both of which facilitate managerial bad news hoarding (Kim et al. 2011a; Kim et al. 2016).

Consequently, we predict that the impact of director networks on future crash risk is more salient when a firm's CEO has more power or ability to suppress information by withholding firm-specific bad news. Rooted in prior research (e.g., Abernethy et al. 2015; Finkelstein 1992; Coles et al. 2014; Lisic et al. 2016), we employ principal component analysis to determine a unidimensional construct from the following six items: (i) the number of board committees on which the CEO serves; (ii) the length of the CEO's tenure; (iii) whether CEO is a company founder; (iv) board size; (v) the fraction of directors appointed after the CEO assumes office (i.e. co-opted directors); and (vi) the equity stakes held by the largest five institutional investors. We create a factor score that weighs the relative importance of each of the observed items (*CEO_POWER*). The value of the composite measure increases with the level of CEO power. We follow Demerjian, Lev and McVay (2012) by gauging CEO ability (*CEO_ABILITY*) based on their efficiency at generating greater output from a given set of inputs. We re-estimate Equation (4) after separately interacting *CONNECTEDNESS* and *BOARD_CEO_TIE* with *CEO_POWER* and *CEO_ABILITY*.

We provide the regression results in Table 4. The estimate coefficients on the interaction term *CONNECTEDNESS* CEO_POWER* are negative and significant at the 10%, 5% and 1% levels across the three crash risk specifications. Similarly, the interaction term *CONNECTEDNESS* CEO_ABILITY* loads negatively at the 10% and 5% levels for $DUVOL_{T+1}$ and $COUNT_{T+1}$, respectively, although this variable is statistically indistinguishable from zero when we specify $NCSKEW_{T+1}$ as the dependent variable. This evidence implies that the role that director external social networks play in shaping future crash risk varies systematically with CEO characteristics. In contrast, we do not obtain similar results when we interact *BOARD_CEO_TIE* with *CEO_POWER* and *CEO_ABILITY*, respectively.

4.2.2 External Monitoring by Professional Auditors

Extensive prior research suggests that litigation and reputation concerns motivate professional auditors to closely monitor clients' reporting choices that might mask bad news versus good news (e.g., Lys and Watts 1994; Heninger 2001; Barron, Pratt, and Stice 2001). Callen and Fang (2017) find robust evidence that the term of the auditor-client relationship is negatively related to one-year-ahead stock price crash risk. Their analysis lends support to the monitoring-by-learning perspective in that development of client-specific knowledge over the course of the auditor-client relationship enhances auditors' ability to detect and deter bad news hoarding activities, thereby reducing future crash risk.

Moreover, extant research suggests that, relative to non-specialist auditors, industry specialist auditors, which focus intently on developing their expertise and protecting their valuable reputations, conduct higher-quality audits (e.g., Knechel, Naiker, and Pacheco 2007; Lim and Tan 2008; Reichelt and Wang 2010). Relevant to our research questions, Robin and Zhang (2015) report an inverse relation between auditor industry specialization and stock price crash risk, implying that high-quality auditors can directly benefit investors by reducing tail risk. We expect that the impact of director networks on future crash risk is less salient for firms with strong external monitoring measured by longer audit-client relationships and the presence of specialist auditors given that managers in these firms likely have a narrower scope to engage in bad news hoarding. We examine this issue by re-estimating Equation (4) after adding the interaction terms *CONNECTEDNESS *TENURE*, *CONNECTEDNESS *SPEC*, *BOARD_CEO_TIE *TENURE* and *BOARD_CEO_TIE *SPEC*.

The results reported in Table 5 include that the coefficient estimates on the interaction term *CONNECTEDNESS*TENURE* are positive and significant at the 5% level or better across all three crash risk specifications. Similarly, we find that the estimate coefficients on the interaction term *CONNECTEDNESS*SPEC* are positive and significant at the 10% level or better. This evidence implies that the importance of director external social networks to crash risk varies with the strength of external monitoring by professional auditors. In sharp contrast, we find that the interactions of *BOARD_CEO_TIE* with *TENURE* and *SPEC* have no perceptible impact.

4.2.3 Protection of Shareholders' Rights

Shleifer and Vishny (1997) suggest that the protection of shareholders' rights plays a major role in persuading directors to strictly monitor managers. We expect that the impact of director networks on future crash risk is concentrated in firms subject to the stronger investor protection. We initially capture investor protection with the governance index (*GINDEX*) derived by Gompers, Ishii, and Metrick (2003), which is based on a count of 24 antitakeover provisions set by the Investor Responsibility Research Center (IRRC).[21] Higher value of *GINDEX* reflect lax

[21] The IRRC collects and reports data about every two years (1990, 1993, 1995, 1998, 2000, 2002, 2004, and 2006). Like Gompers et al. (2003), we assume that the index remains constant in the year(s) following the most recent report for years in which IRRC does not report *GINDEX*.

corporate governance, fewer shareholder rights, and poor shareholder protection. We code *LO_G* as one for observations having a *GINDEX* value below the sample median, and zero otherwise.

Our second measure of investor protection is based on the staggered adoption of universal demand laws (UDL) at the state level. Houston, Lin, and Xie (2015) suggest that the enactment of universal demand law compromises shareholders' litigation rights against corporate management by adding significant obstacles to derivative lawsuits, causing shareholders to experience worse agency conflicts. They find that in the aftermath of the passage of UDL, firms' equity financing costs rise and their accounting transparency deteriorates. We set *NOUDL* to one if a firm is headquartered in a state that has not adopted universal demand law by year *T*, and zero otherwise. We re-estimate Equation (4) after separately interacting *CONNECTEDNESS* and *BOARD_CEO_TIE* with *LO_G* and *NOUDL*.

In Table 6, we find that the coefficient estimates on the interaction term *CONNECTEDNESS*LO_G* enter negatively at the 5% level or better across all three crash risk specifications. Similarly, the interaction term *CONNECTEDNESS*NOUDL* is negative and significant at the 10% level or better. This evidences implies that director external social networks have more impact on future crash risk when investor protection is stricter. However, these results do not extend to interacting *BOARD_CEO_TIE* with *LO_G* and *NOUDL* in successive regressions.

Altogether, the results in Tables 4 to 6 suggest that better informed directors are more capable of restricting bad news hoarding in the presence of more intensive agency conflicts stemming from managerial power, weaker monitoring by external auditors, and tougher shareholders protection. The evidence collectively supports the monitoring view as an explanation for the main findings.

4.2.4 Director Characteristics

Next, we examine whether the role that director networks play in shaping future crash risk is sensitive to director characteristics. In particular, we expect to observe that directors with stronger incentives to monitor and directors who stand to benefit more from information stemming from networks are more likely to take advantage of their external social networks to detect and constrain managerial bad news hoarding, with concomitant implications for subsequent stock price crash risk. Analyzing this issue involves decomposing our measure of director external social networks (*CONNECTEDNESS*) into these four distinct classifications: (i) independent directors (*CONNECTEDNESS_IndepD*) versus non-independent directors (*CONNECTEDNESS_NonIndepD*); (ii) audit-committee directors (*CONNECTEDNESS_AuditComD*) versus non-audit-committee directors (*CONNECTEDNESS_NonAuditComD*); (iii) short-tenured directors (*CONNECTEDNESS_ShortTenD*) versus long-tenured directors (*CONNECTEDNESS_LongTenD*); and (iv) high-reputation directors (*CONNECTEDNESS_HighRepD*) versus low-reputation directors (*CONNECTEDNESS_LowRepD*). We classify directors as having short (long) tenure if his/her tenure with the current role is below (above) the sample median, and classify directors as having high (low) reputation if the total number of his/her directorship held at other public and private companies is among the top quartile (the bottom three quartiles) of the sample distribution. We anticipate greater monitoring incentives for independent directors, audit committee members, and high-reputation directors due to their fiduciary responsibility and reputation concern, and greater benefits for short-tenure directors due to their lack of firm-specific knowledge. We then estimate an expanded version of Equation (4) by including director external network measures for each pair of partitions.

In Table 7, the coefficient estimates on the connectedness of independent directors (*CONNECTEDNESS_IndepD*), audit committee directors (*CONNECTEDNESS_AuditComD*), short-tenured directors (*CONNECTEDNESS_ShortTenD*), and high-reputation directors

(*CONNECTEDNESS_HighRepD*) are all significant at the 10% level or better across all 12 specifications. However, the coefficient estimates on the connectedness for non-independent directors (*CONNECTEDNESS_NonIndepD*), non-audit committee directors (*CONNECTEDNESS_NonAuditComD*), long-tenured directors (*CONNECTEDNESS_ LongTenD*), and low-reputation directors (*CONNECTEDNESS_LowRepD*) are significant at the 10% level or better only among six out of the 12 specifications. In almost all comparisons (Model 11 is the lone exception), the economic magnitude of the coefficients on the connectedness terms for monitoring-type directors are larger than that for non-monitoring-type directors. The evidence lends additional support for the monitoring perspective as the primary mechanism at work.

4.2.5 Verification of Bad News Hoarding

The premise underlying the relation between director social networks and crash risk is that these networks influence managerial bad news hoarding. However, we naturally cannot directly observe whether managers engage in bad news hoarding. In order to help empirically validate the underlying premise, we examine whether director social networks are associated with several bad-news-hoarding channels or signals documented in prior research (Hutton et al. 2009; Kim et al. 2011a; Callen and Fang 2015b; Zhu 2016; Francis et al. 2016): (i) opaque financial reporting (*OPAQUE*); (ii) positive and negative discretionary accruals (*POS_DA* and *NEG_DA*); (iii) meeting and beating analyst forecasts using discretionary accruals (*MBEAT*); (iv) real earnings management (*ABN_PROD, ABN_DISEXP,* and *ABN_CFO*); (v) tax avoidance (*CASH_ETR*); and (vi) short interest ratio (*SIR*).

In this analysis, we regress the variables listed above on the two measures of director social networks (i.e., *CONNECTEDNESS* and *BOARD_CEO_TIE*), a series of firm characteristics variables in Equation (4), and industry and year fixed effects. In Table 8, we generally find that firms with a higher value of *CONNECTEDNESS* are associated with lower opaqueness, lower positive and negative discretionary accruals, a lower probability of meeting/beating analyst forecasts via discretionary accruals, lower abnormal production, greater discretionary expenditures, and a lower short interest ratio (t-statistics= -1.75, -5.55, -1.80, -2.15, -3.79, 2.58, and -3.18, respectively). The evidence is consistent with a negative link between director external social networks and channels/signals for bad news hoarding, lending additional support to the monitoring view as an explanation for the main results. In stark contrast, we do not observe any negative relations between *BOARD_CEO_TIE* and the bad-news-hoarding variables in Table 8.

4.3 Cross Sectional Analyses - Information Leakage Explanation

Although the results reported earlier provide strong, robust support for the monitoring explanation, these findings do not rule out the non-mutually-exclusive information leakage explanation. Accordingly, we next conduct additional analyses to examine whether the documented negative relation between director social networks and stock price crash risk reflects information leakage from directors to outsiders as well.

We conjecture that for firms with a higher level of informed trading, information leakage from directors to outsiders is more likely to occur, implying that the impact of social networks on crash risk will be larger in this situation. After prior research (e.g., Brown and Hillegeist 2007; Akbas et al. 2016), we measure informed trading with these four variables: (i) the short interest ratio (*SIR*); (ii) the ratio of total monthly put and call trading volume to stock trading volume (*OPTION/STOCK VOL*); (iii) the probability of informed tradinge (*PIN*);[22] and (iv) insider trades (*INS_TRADE*), which is the dollar value of net insider trading, scaled by firm size.[23] We re-

[22] We obtain the PIN data from http://scholar.rhsmith.umd.edu/sbrown/pin-data.
[23] In another specification, we include the interactions between *CONNECTEDNESS* and *BOARD_CEO_TIE* with institutional ownership. The results on the interaction terms remain insignificant.

estimate Equation (4) after interacting *CONNECTEDNESS* and *BOARD_CEO_TIE* with each of the four informed trading measures in successive regressions.

In Table 9, we find that all of the coefficient estimates on the interaction terms between *CONNECTEDNESS* and the measures of informed trading are statistically insignificant at conventional levels across all three crash risk specifications. Similarly, almost all of the coefficient estimates on the interaction terms between *BOARD_CEO_TIE* and the measures of informed trading are insignificant across all the three crash risk specifications. This evidence suggests that director social networks do not play a more pronounced role in shaping future crash risk in the presence of a higher level of informed trading. Collectively, our analyses provide strong support for the monitoring view and no support for the information leakage view.

4.4 Endogenous director-company match

Director networks are routinely formed through their educational, professional, and civic experience long before they join the company, implying that it is unlikely that firm characteristics shape director networks. However, as directors with large networks may refrain from serving on boards of firms with serious stock price crash risk given their reputation and litigation concerns, it is important to confront that our core evidence may spuriously stem from the endogenous match between companies and directors. In the main tests, we rely on residual connections to temper the impact of firm size, board size, firm age, analyst coverage, and institutional ownership. Next, we further tackle threat to reliable inference of other firm characteristics that may drive the director-company match.

4.4.1 Director retirement

In a difference-in-difference (DID) identification strategy, we exploit the exogenous reduction in director networks arising from director retirement (Fracassi and Tate 2012; Fracassi

2017; Ke, Li, Ling, and Zhang 2017).[24] This design effectively controls for time-invariant differences between the treatment and control firms, as well as for time-variant trends that are common to both groups. If directors with large networks play a more critical role in constraining bad news hoarding, then we would expect a larger increase in crash risk for firms whose directors have larger connections before their retirement. We follow Ke et al. (2017) in coding a director as retired if he/she departs the board at the age of 65 or older. To help dispel the concern that the evidence reflects shifting sample composition, we require each firm to have at least one observation during both the pre- and post-retirement year. Among the 211 director retirement with requisite data, the mean (median) value of director connections is 473 (142) before they retire. We set *POSTRETIRE* to 1 for the first year after the retirement, 0 for the last year before the retirement, and set *LARGE_DECREASE* to 1 (0) for directors with above (below) the median value of network size before retirement. In Table 10, we report in Columns (1)-(3) of Panel A that the coefficient for *POSTRETIRE*LARGE_DECREASE* enters positively in all three regressions, implying that crash risk rises for firms that lose retiring directors with extensive connections.[25]

Central to justifying the DID design is validating the parallel trends assumption under which we expect no differential trend in crash risk between the treatment and control groups absent the shock from director retirement. After Lennox (2016), we focus on observations from the pre-retirement period and regress crash risk on *LARGE_DECREASE*, *TREND*, and

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[24] Some recent research relies on director deaths as an exogenous shock to board structure (Fracassi and Tate 2012; Fracassi 2017; Ke et al. 2017). Data constraints prevent us from examining director deaths since connections are set to zero for the entire sample period in BoardEx for directors who died.

[25] It is possible that firms appointing more reputable directors have higher average connections per director and naturally suffer greater loss of connections upon director retirement, and that such firms are inherently different from firms that lose fewer connections at director retirement. We find between these two groups of firms, there is no significant difference in the average director connections, average director age, or any of the control variables used in our main regression, with the only exception being *KUR* which is higher for the treatment firms at the 10% significance level. Accordingly, the treatment sample is well-matched against the control sample, which is important since the parallel trends assumption is more defensible when firms more closely resemble each other.

*LARGE_DECREASE*TREND*. *TREND* takes the value of -3, -2, and -1 for the corresponding year before retirement. A negative coefficient for the interaction would indicate a decreasing trend in crash risk for the treatment group before the treatment. Untabulated evidence shows that the interaction term has no perceptible impact across all three crash risk measures, providing some assurance that parallel trend assumption is defensible.[26] Although the inclusion of year and industry fixed effects in the DID design differences away any time-varying or industry-specific effects, we further include firm fixed effects to difference away constant unobservable firm-specific attributes. This approach allows the difference between treatment and control group to vary across firms. The firm fixed effects regressions in Columns (4)-(6) yield similar results.[27, 28]

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[26] As an alternate approach, we follow Kausar, Shroff, and White (2016) by comparing the level of crash risk between the two groups during the three-year period before retirement. Consistent with the parallel trends assumption, we fail to find any distinguishable difference between the two groups. To further mitigate the concern that our results stem from trends preceding or following retirement, we deliberately shift the event year to the pre- and post-retirement period. If we continue to observe the treatment effects surrounding the falsified dates, then this would imply that preexisting divergent trends, rather than the impact of director retirement, are responsible for our evidence. Specifically, we compare the treatment and control firms between year t-3 and t-2, t-2 and t-1, t+1 and t+2, t+2 and t+3 by designating the second year in each pair as the pseudo retirement year. In unreported results, we find in 11 of the 12 regressions (i.e., four comparisons across three crash risk measures) that the term *LARGE_DECREASE*POST* fails to load; we attribute the lone exception to random variation. Collectively, reinforcing our earlier evidence, the DID results likely reflect outcomes stemming from director retirements, rather than the role of other forces.

[27] We do not use firm fixed effects regression, which exploit within-firm changes in the dependent and independent variables across time, for the full sample of 28,531 observations. Reflecting that board composition is typically quite sticky across time, 42% observations in the full sample experience no change in the raw value of director total connections from year t-1 to t. The mean within-firm standard deviation of *CONNECTEDNESS* is only 38% of the corresponding standard deviation for the full sample. Such persistence in director connections leads to insufficient within-firm variation, undermining the power of a firm fixed effects regression in this setting.

[28] In an alternative method, we exploit the relative exogenous shift in board composition stemming from merger and acquisition (M&A) activities. We restrict the analysis to the subsample of firms with M&A identified through the SDC Platinum database. To focus on material M&A, we rely on completed deals greater than $10 million and for which the acquirer owns 100% of the target firm after the transaction (Masulis, Wang, Xie 2007). To implement a DID design, we set *POSTMA* to 1 (0) for the year immediately after (before) the M&A transaction, and set *LARGE_INCREASE* to 1 if the change in the acquirer board network size is above the sample median value, and 0 otherwise. The interaction term *POSTMA_LARGE_INCREASE* captures the incremental change in crash risk for acquirers with larger increases in director networks from the pre- to post-M&A period relative to acquirers with smaller increases. In untabulated evidence, we find that *POST_LARGE_INCREASE* loads negatively in two of the three crash risk regressions. Overall, we observe some evidence that acquirers with a larger increase in director networks enjoy a steeper decline in crash risk from the pre- to post-merger and acquisition period.

4.4.2 Stock price crash risk and subsequent changes in director networks

The alternative explanation of endogenous director-company match predicts a negative association between future changes in director networks and past crash risk. After recent research on board attributes (Badolato, Donelson, and Ege 2014; Larcker et al. 2013), we directly test this explanation by regressing changes in director networks from year t-1 to t (Δ*CONNECTEDNESS*) on the lagged values of three measures of crash risk and all control variables in Equation (4). We use the prior-year crash risk since it is observable to directors who contemplate joining or departing the company. In Table 10 Panel B, we find in Columns (1)-(3) that the coefficients on all three lagged crash risk variables are statistically insignificant and nearly identically zero. It is possible that only more reputable directors with large networks and, in turn, more employment options are more selective concerning the boards on which to serve. In an untabulated test, we restrict the analysis to observations with the addition or departure of directors whose network size is above the sample median value, and find that the three lagged crash risk variables remain insignificant. Overall, we fail to find any evidence that directors with large networks are less likely to match with firms with greater ex ante stock price crash risk, inconsistent with endogenous director-company match driving our main results.

5. Conclusions

The agency costs perspective of manager bad news hoarding proposed by Jin and Myers (2006) is a widely-accepted explanation for future stock price risk. However, despite the large crash risk literature built on this premise, evidence on whether information from alternate channels weakens the manager's control of bad news remains scarce. We help fill this void by analyzing whether boards with large social networks, which potentially facilitates information sharing, better constrain the bad new hoarding responsible for future stock price crashes.

Our analysis suggests that the external networks of the boards effectively attenuate future crash risk, with this link varying predictably with firm and director characteristics. At the firm level, the results are more pronounced for firms with more powerful and competent CEOs who are more capable at withholding bad news, and firms subject to stronger shareholder protection rights; also consistent with expectations, the results are weaker for firms enjoying stricter monitoring from their auditors. At the director level, our evidence is mainly driven by directors who: have stronger incentives or responsibility to monitor, will benefit more due to their lack of firm-specific knowledge, and have more valuable reputations to protect. Exploring the underlying channels, we find that director external social connections are negatively associated with a battery of channels and signals for bad news hoarding. We fail to find evidence that our main results are driven by firms with greater informed trading. Collectively, we provide robust evidence consistent with the monitoring view and no empirical support for the information leakage view. We also find that CEO-director social connections have a negative, although considerably weaker, association with future stock price risk.

Overall, the evidence suggests that information exchange via director networks weakens the information monopoly of the manager, constraining them from suppressing bad news that, in turn, engenders stock price crash risk. Future research could explore how internet information intermediaries, who have positive capital market impacts (Drake, Thornock, and Twedt 2017), facilitate the flow of information. This analysis could broaden our understanding of the role that alternative information channels play in shaping stock price crash risk.

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Appendix A
Variable definitions

Measures of Stock Price Crash risk:

NCSKEW is the negative coefficient of skewness of firm-specific daily returns over the fiscal year.

DUVOL is the log of the ratio of the standard deviation of firm-specific daily returns for the "down-day" sample to standard deviation of firm-specific daily returns for the "up-day" sample over the fiscal year.

COUNT is the number of firm-specific daily returns exceeding 3.09 standard deviations below the mean firm-specific daily return over the fiscal year, minus the number of firm-specific daily returns exceeding 3.09 standard deviations above the mean firm-specific daily return over the fiscal year; 3.09 represents frequencies of 0.1 percent in the normal distribution.

We estimate firm-specific daily returns from an expanded market and industry index model regression for each firm and year (Hutton et al. 2009):

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \varepsilon_{j,t},$$

where $r_{j,t}$ is the return on stock j in day t, $r_{m,t}$ is the return on the *CRSP* value-weighted market index in day t, and $r_{i,t}$ is the return on the value-weighted industry index based on the two-digit SIC code. The firm-specific daily return is the natural log of one plus the residual return from the regression model above.

Measures of Director External and Internal Social Networks:

CONNECTEDNESS is the regression residual obtained from regressing the natural logarithm of aggregate director connections on the natural logarithm of firm size, board size, firm age, number of analysts, and on institutional ownership.

BOARD_CEO_TIE is the natural logarithm of total number of board members' connections with the CEO through prior education.

Other variables:

KUR is the kurtosis of firm-specific daily returns over the fiscal year.

SIGMA is the standard deviation of firm-specific daily returns over the fiscal year.

RET is the cumulative firm-specific daily returns over the fiscal year, multiplied by 100.

MB is the ratio of market value of equity to book value of equity at the end of the fiscal year.

LEV is the book value of all liabilities divided by total assets at the end of the fiscal year.

LNSIZE is the log value of market capitalization at the end of the fiscal year.

ROA is the operating earnings divided by total assets at the end of the fiscal year.

DTURN is the average monthly share turnover over the fiscal year minus the average monthly share turnover over the previous year, where monthly share turnover is calculated as the monthly share trading volume divided by the number of shares outstanding over the month.

OPAQUE is the 3-year moving sum of the absolute value of annual performance-adjusted discretionary accruals developed by Kothari et al. (2005).

ABN_PROD is the abnormal level of production costs developed by Roychowdhury (2006).

ABN_DISEXP is the abnormal level of discretionary expenditures developed by Roychowdhury (2006).

ABN_CFO is the abnormal level of cash flow from operations developed by Roychowdhury (2006).

DIV is an indicator equal to one if a firm has dividend payout for the fiscal year, and zero otherwise.

TENURE is the number of consecutive years in the fiscal year that the auditor has been employed by the firm (in the case of audit firm mergers, the incumbent auditor–client relationship is considered to be the continuation of the prior auditor).

AGE is the number of years that the firm has been listed on *Compustat* since 1950.

BIGN is equal to 1 if a firm is audited by a Big-4 auditor (or its predecessor), and zero otherwise.

SPEC is equal to one when an auditor has the largest industry market share in the fiscal year, and zero otherwise.

ANA is the log value of one plus the number of analysts that issue earnings forecasts for a given firm during the fiscal year.

SIR is the number of shares sold short divided by total shares outstanding from the last month of fiscal year, with a range from 0 to 1. Compustat Supplemental Short Interest File provides the available data to calculate short interest.

INST is the percentage of a specific firm's equity held by institutional investors at the end of the fiscal year.

DISTANCE equals to one if the distance between the county where a firm is headquartered and the closest SEC regional or national office is within 100 km, and zero otherwise.

CEO_POWER is a composite measure based on principal component analysis of: (i) the number of board committees on which the CEO serves; (ii) the length of the CEO's tenure; (iii) whether the CEO is a company founder; (iv) board size; (v) the proportion of board members who are appointed after the CEO assumes his office (i.e., co-opted directors); and (vi) the percentage of shares owned by the largest five institutional investors of the firm.

CEO_ABILITY is a continuous measure of CEO ability developed in Demerjian, Lev and McVay (2012).

LO_G equals to one if the index of Gompers et al (2003) is less than the sample median, and zero otherwise.

NOUDL equals to one if the firm is headquartered in a state without the state-level adoption of universal demand law in the current year, and zero otherwise.

OPTION/STOCK VOL is the ratio of total monthly put and call trading volume to stock trading volume.

PIN is the probability of informed trade developed by Brown and Hillegeist (2007).

INS_TRADE is the value of net insider sells divided by firm size.

POS_DA is equal to performance-adjusted discretionary accruals if its value is greater than zero, and zero otherwise.

NEG_DA is equal to performance-adjusted discretionary accruals if its value is less than zero, and zero otherwise.

MBEAT equals to one if positive performance-adjusted discretionary accruals are used to meet or beat analyst earnings forecast, and zero otherwise, based on Davis, Soo, and Trompeter (2009).

CASH_ETR is cash taxes paid scaled by pretax book income after removing the effects of special items.

Table 1
Descriptive Statistics

This table presents descriptive statistics of key variables of interest for the sample of firms included in our study. The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. Panel A presents descriptive statistics; Panel B presents a Pearson correlation matrix. Bold values indicate statistical significance at the 1% level. All variables are defined in Appendix A.

Panel A: Descriptive Statistics

	N	Mean	Standard Dev.	Q1	Median	Q3
$NCSKEW_{T+1}$	28531	-0.0794	1.7088	-0.6964	-0.1326	0.4484
$DUVOL_{T+1}$	28531	-0.1194	0.6988	-0.5108	-0.1306	0.2658
$COUNT_{T+1}$	28531	-0.3229	1.7397	-1.0000	0.0000	1.0000
CONNECTEDNESS	28531	0.0015	0.6015	-0.3320	0.0603	0.3941
BOARD_CEO_TIE	28531	0.3028	0.3697	0.0000	0.0000	0.6931
NCSKEW	28531	-0.0127	1.4914	-0.6508	-0.1335	0.4200
KUR	28531	8.7231	12.6763	2.2205	4.4441	9.6831
SIGMA	28531	0.0272	0.0152	0.0169	0.0237	0.0338
RET	28531	-0.0005	0.0010	-0.0006	-0.0003	-0.0001
MB	28531	3.3054	4.2061	1.3940	2.2029	3.6349
LEV	28531	0.4540	0.2126	0.2847	0.4539	0.6059
LNSIZE	28531	20.2392	1.9206	18.9237	20.2293	21.5448
ROA	28531	0.0961	0.1680	0.0629	0.1168	0.1693
DTURN	28531	0.0034	0.0987	-0.0295	0.0011	0.0344
OPAQUE	28531	0.1694	0.1432	0.0804	0.1300	0.2087
ABN_PROD	28531	-0.0375	0.2221	-0.1522	-0.0373	0.0682
ABN_DISEXP	28531	-0.0828	0.3025	-0.2417	-0.0825	0.0387
ABN_CFO	28531	0.0622	0.1697	-0.0171	0.0542	0.1411
DIV	28531	0.3668	0.4819	0.0000	0.0000	1.0000
TENURE	28531	11.6048	9.0610	5.0000	9.0000	16.0000
AGE	28531	20.0645	10.0364	11.0000	18.0000	29.0000
BIGN	28531	0.7873	0.4092	1.0000	1.0000	1.0000
SPEC	28531	0.4158	0.4929	0.0000	0.0000	1.0000
ANA	28531	1.6739	0.9776	0.6931	1.7918	2.4849
SIR	28531	0.0421	0.0558	0.0045	0.0227	0.0554
INST	28531	0.5830	0.3289	0.3195	0.6687	0.8545
DISTANCE	28531	0.4703	0.4991	0.0000	0.0000	1.0000

Panel B: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13
$NCSKEW_{T+1}$	1													
$DUVOL_{T+1}$	2	**0.93**												
$COUNT_{T+1}$	3	**0.49**	**0.67**											
CONNECTEDNESS	4	**-0.03**	**-0.04**	**-0.04**										
BOARD_CEO_TIE	5	**0.02**	**0.03**	**0.02**	**0.08**									
NCSKEW	6	**0.04**	**0.04**	**0.03**	0.00	**0.02**								
KUR	7	**0.02**	0.01	0.00	0.01	-0.01	**0.30**							
SIGMA	8	**-0.05**	**-0.09**	**-0.09**	**0.07**	**-0.13**	**-0.03**	**0.15**						
RET	9	**0.04**	**0.06**	**0.06**	**-0.04**	**0.07**	**0.06**	**-0.11**	**-0.74**					
MB	10	**0.04**	**0.04**	**0.03**	0.00	**0.04**	**-0.05**	0.00	**-0.02**	0.00				
LEV	11	0.00	0.01	0.01	**0.09**	**0.09**	0.00	0.01	**-0.08**	**0.02**	**0.25**			
LNSIZE	12	**0.11**	**0.13**	**0.13**	**-0.02**	**0.30**	**0.07**	0.00	**-0.55**	**0.29**	**0.19**	**0.21**		
ROA	13	**0.06**	**0.09**	**0.10**	**-0.13**	**0.09**	**0.05**	**-0.03**	**-0.38**	**0.24**	**-0.02**	**0.06**	**0.34**	
DTURN	14	**0.03**	**0.03**	**0.02**	**-0.02**	0.01	**0.01**	**0.10**	**0.16**	**-0.11**	**0.05**	**0.04**	**0.02**	**0.04**
OPAQUE	15	0.01	0.00	-0.01	-0.01	**-0.07**	**-0.02**	0.01	**0.30**	**-0.16**	**0.10**	**-0.07**	**-0.24**	**-0.16**
ABN_PROD	16	-0.01	0.00	-0.01	**-0.04**	**-0.02**	0.00	**-0.03**	0.00	0.00	**-0.18**	**0.16**	**-0.09**	**-0.11**
ABN_DISEXP	17	-0.01	**-0.02**	**-0.02**	**0.09**	**-0.04**	**-0.04**	-0.01	**0.19**	**-0.11**	**0.14**	**-0.04**	**-0.14**	**-0.20**
ABN_CFO	18	**0.04**	**0.06**	**0.06**	**-0.08**	**0.07**	**0.04**	**0.03**	**-0.20**	**0.11**	**0.07**	**-0.15**	**0.28**	**0.44**
DIV	19	**0.03**	**0.06**	**0.06**	**-0.07**	**0.10**	**0.03**	**-0.04**	**-0.38**	**0.18**	-0.01	**0.16**	**0.36**	**0.25**
TENURE	20	**0.02**	**0.03**	**0.04**	**0.03**	**0.12**	**0.02**	0.00	**-0.28**	**0.13**	0.00	**0.14**	**0.36**	**0.14**
AGE	21	**-0.02**	0.01	**0.02**	0.01	**0.04**	**-0.02**	**-0.02**	**-0.29**	**0.14**	**-0.08**	**0.14**	**0.20**	**0.15**
BIGN	22	**0.06**	**0.07**	**0.07**	**0.07**	**0.16**	**0.09**	**0.02**	**-0.26**	**0.15**	**0.05**	**0.18**	**0.52**	**0.15**
SPEC	23	**0.03**	**0.03**	**0.03**	**0.05**	**0.10**	**0.04**	0.01	**-0.15**	**0.08**	**0.03**	**0.07**	**0.28**	**0.08**
ANA	24	**0.10**	**0.12**	**0.12**	**-0.02**	**0.27**	**0.14**	**0.04**	**-0.38**	**0.21**	**0.13**	**0.15**	**0.80**	**0.25**
SIR	25	**0.05**	**0.05**	**0.05**	**-0.04**	**0.04**	**0.07**	**0.08**	**-0.10**	**0.07**	**0.09**	**0.05**	**0.19**	**0.10**
INST	26	**0.07**	**0.09**	**0.09**	**-0.03**	**0.13**	**0.10**	**0.05**	**-0.39**	**0.22**	**0.02**	**0.11**	**0.51**	**0.26**
DISTANCE	27	**-0.02**	**-0.03**	**-0.03**	**0.10**	0.01	-0.01	**0.02**	**0.04**	**-0.03**	**0.04**	**-0.03**	**-0.04**	**-0.06**

		14	**15**	**16**	**17**	18	19	**20**	**21**	**22**	**23**	**24**	**25**	**26**
OPAQUE	15	**0.02**												
ABN_PROD	16	**-0.02**	**0.01**											
ABN_DISEXP	17	**0.05**	**0.16**	**-0.46**										
ABN_CFO	18	**0.02**	**-0.11**	**-0.38**	**-0.34**									
DIV	19	**0.01**	**-0.20**	**0.04**	**-0.11**	0.06								
TENURE	20	**0.00**	**-0.18**	**0.02**	**-0.09**	0.07	0.33							
AGE	21	**-0.01**	**-0.21**	**0.09**	**-0.14**	0.02	0.42	**0.48**						
BIGN	22	**0.01**	**-0.17**	**-0.04**	**-0.06**	0.11	0.15	**0.31**	**-0.02**					
SPEC	23	**-0.01**	**-0.11**	**0.01**	**-0.04**	0.04	0.07	**0.20**	**0.02**	**0.44**				
ANA	24	**-0.01**	**-0.19**	**-0.10**	**-0.08**	0.23	0.16	**0.24**	**0.01**	**0.47**	**0.25**			
SIR	25	**0.12**	**0.00**	**-0.07**	**0.05**	0.07	-0.03	**0.01**	**-0.05**	**0.15**	**0.07**	**0.28**		
INST	26	**0.01**	**-0.21**	**-0.05**	**-0.10**	0.19	0.12	**0.18**	**0.09**	**0.38**	**0.19**	**0.56**	**0.38**	
DISTANCE	27	**-0.01**	**0.02**	**-0.08**	**0.03**	0.01	-0.06	**-0.05**	**-0.05**	**-0.05**	**-0.05**	**-0.05**	**-0.03**	**-0.05**

Table 2
Impact of Director Social Networks on Crash Risk

This table estimates the pooled cross-sectional regression of future stock price crash risk on director networks. The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. *t*-statistics reported in parentheses are based on White standard errors corrected for firm clustering. Year and industry fixed-effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Dependent Variable=	$NCSKEW_{T+1}$		$DUVOL_{T+1}$		$COUNT_{T+1}$	
	Model 1		**Model 2**		**Model 3**	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
TEST VARAIBLES						
CONNECTEDNESS	-0.0550***	(-3.08)	-0.0294***	(-3.99)	-0.0550***	(-3.01)
BOARD_CEO_TIE	-0.0460	(-1.52)	-0.0219*	(-1.74)	-0.0794**	(-2.53)
CONTROL VARIABLES						
NCSKEW	0.0147*	(1.83)	0.0068**	(2.13)	0.0090	(1.22)
KUR	0.0022**	(2.22)	0.0005	(1.22)	0.0007	(0.82)
SIGMA	-0.4900	(-0.29)	-1.3882**	(-2.07)	-3.6194**	(-2.03)
RET	24.1777	(1.14)	4.3162	(0.50)	6.2940	(0.29)
MB	0.0107***	(3.45)	0.0040***	(3.54)	0.0080***	(3.00)
LEV	-0.2079***	(-3.66)	-0.0936***	(-4.01)	-0.2670***	(-4.55)
LNSIZE	0.0637***	(5.44)	0.0250***	(5.13)	0.0594***	(4.75)
ROA	0.2187**	(2.31)	0.1752***	(4.79)	0.5216***	(5.70)
DTURN	0.3240***	(3.02)	0.1711***	(3.85)	0.3187***	(2.82)
OPAQUE	0.3041***	(3.69)	0.1235***	(3.75)	0.2521***	(3.06)
ABN_PROD	0.2593***	(3.58)	0.1287***	(4.39)	0.2384***	(3.28)
ABN_DISEXP	0.1592***	(2.87)	0.0634***	(2.89)	0.1060**	(1.99)
ABN_CFO	0.1406	(1.49)	0.0671*	(1.77)	0.1077	(1.10)
DIV	0.0249	(0.94)	0.0233**	(2.17)	0.0152	(0.57)
TENURE	-0.0024*	(-1.73)	-0.0012**	(-2.03)	-0.0030**	(-2.08)
AGE	-0.0014	(-1.02)	-0.0002	(-0.36)	0.0004	(0.27)
BIGN	-0.0172	(-0.51)	-0.0134	(-1.00)	-0.0212	(-0.62)
SPEC	0.0020	(0.08)	0.0024	(0.24)	0.0085	(0.36)
ANA	0.0424**	(2.24)	0.0224***	(2.83)	0.0561***	(2.78)
SIR	0.4659**	(2.09)	0.1143	(1.27)	0.2334	(1.06)
INST	0.1010**	(2.43)	0.0369**	(2.15)	0.0996**	(2.25)
DISTANCE	-0.0482**	(-2.18)	-0.0303***	(-3.37)	-0.0743***	(-3.38)
INTERCEPT	-1.0603***	(-4.58)	-0.3894***	(-4.04)	-0.9278***	(-3.59)
Year fixed effects	YES		YES		YES	
Industry fixed effects	YES		YES		YES	
N	28531		28531		28531	
adj. R-sq	0.0270		0.0479		0.0445	

Table 3

Robustness Checks: Sensitivity Tests

This table re-estimates Equation (4) for the pooled cross-sectional regression of future stock price crash risk on director social networks. Results are presented separately for each of our measures of stock price crash risk in Panels A, B and C. Model 1 re-specifies external social networks with the raw value of connectedness. Models 2-5 control for De Franco, Kothari, and Verdi (2011)'s comparability measure, Dechow and Dichev (2002)'s accrual quality measure as modified by Francis et al. (2005), Dechow, Ge, Larson and Sloan (2011)'s F-score measure, and cash effective tax rate, respectively. In Models 6 and 7, we present the estimation results after separating our sample into high and low tercile groups based on lead firm-specific stock performance. To economize on space, all of the control variables (see Table 2) are suppressed. The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. We report t-statistics in parentheses, based on White standard errors corrected for firm clustering. All models include year and industry fixed-effects. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Panel A: *NCSKEW*$_{T+1}$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Raw value of Connectedness	**Control for Comparability**	**Control for DD Accrual**	**Control for F-score**	**Control for Tax Avoidance**	**Low Lead Performance Group (Bottom Tercile)**	**High lead Performance Group (Top Tercile)**
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.0467***	-0.0571**	-0.0538***	-0.0521***	-0.0527**	-0.1032***	0.0059
	(-2.95)	(-2.44)	(-2.98)	(-2.81)	(-2.48)	(-3.12)	(0.23)
BOARD_CEO_TIE	-0.0464	-0.0730*	-0.0450	-0.0532*	-0.0265	-0.1194*	0.0477
	(-1.53)	(-1.87)	(-1.49)	(-1.68)	(-0.77)	(-1.91)	(1.17)
Controls	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES
N	28531	17705	28328	26186	21691	9510	9511
adj. R-sq	0.0270	0.0261	0.0260	0.0277	0.0242	0.0744	0.0155

Panel B: $DUVOL_{T+1}$

	Model 1 Raw value of Connectedness	**Model 2** Control for Comparability	**Model 3** Control for DD Accrual	**Model 4** Control for F-score	**Model 5** Control for Tax Avoidance	**Model 6** Low Lead Performance Group (Bottom Tercile)	**Model 7** High lead Performance Group (Top Tercile)
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.0248***	-0.0272***	-0.0291***	-0.0293***	-0.0272***	-0.0469***	-0.0028
	(-3.83)	(-2.80)	(-3.88)	(-3.79)	(-3.08)	(-3.61)	(-0.22)
BOARD_CEO_TIE	-0.0221*	-0.0337**	-0.0218*	-0.0210	-0.0144	-0.0475**	0.0089
	(-1.76)	(-2.08)	(-1.73)	(-1.60)	(-1.00)	(-2.01)	(0.46)
Controls	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES
N	28531	17705	28328	26186	21691	9510	9511
adj. R-sq	0.0478	0.0468	0.0467	0.0480	0.0416	0.1050	0.0323

Panel C: $COUNT_{T+1}$

	Model 1 Raw value of Connectedness	**Model 2** Control for Comparability	**Model 3** Control for DD Accrual	**Model 4** Control for F-score	**Model 5** Control for Tax Avoidance	**Model 6** Low Lead Performance Group (Bottom Tercile)	**Model 7** High lead Performance Group (Top Tercile)
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.0513***	-0.0507**	-0.0594***	-0.0596***	-0.0509**	-0.0727**	-0.0079
	(-3.18)	(-2.10)	(-3.14)	(-3.04)	(-2.34)	(-2.35)	(-0.23)
BOARD_CEO_TIE	-0.0790**	-0.0903**	-0.0784**	-0.0566*	-0.0579	-0.0746	-0.0607
	(-2.52)	(-2.26)	(-2.49)	(-1.71)	(-1.64)	(-1.33)	(-1.19)
Controls	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES
N	28531	17705	28328	26186	21691	9510	9511
adj. R-sq	0.0445	0.0438	0.0436	0.0453	0.0369	0.0918	0.0266

Table 4
Differential Impact of Director Social Networks on Crash Risk: CEO Characteristics

This table estimates the pooled cross-sectional relation between director social networks, CEO characteristics, and future stock price crash risk. We measure CEO characteristics based on the following two dimensions: CEO power (that is, a composite measure based on principal component analysis in Abernethy, Kuang, and Qin 2015) and CEO ability (i.e., a continuous measure developed in Demerjian, Lev and McVay (2012)). The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. To economize on space, all the control variables (see Table 2) are suppressed. We report *t*-statistics in parentheses, based on White standard errors corrected for firm clustering. All models include year and industry fixed-effects. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.0467	-0.0233*	-0.0309	-0.0092	-0.0032	0.0295
	(-1.64)	(-1.96)	(-1.06)	(-0.23)	(-0.18)	(0.67)
BOARD_CEO_TIE	-0.0372	-0.0192	-0.0760*	-0.0713	-0.0351	-0.0776
	(-0.86)	(-1.08)	(-1.85)	(-1.04)	(-1.19)	(-1.05)
CONNECTEDNESS CEO_POWER*	-0.0336*	-0.0176**	-0.0500***			
	(-1.82)	(-2.39)	(-2.91)			
BOARD_CEO_TIE CEO_POWER*	0.0021	0.0069	0.0140			
	(0.07)	(0.58)	(0.48)			
CEO_POWER	0.0038	-0.0021	-0.0094			
	(0.23)	(-0.30)	(-0.56)			
*CONNECTEDNESS*CEO_ABILITY*				-0.0880	-0.0489*	-0.1603**
				(-1.37)	(-1.81)	(-2.35)
*BOARD_CEO_TIE*CEO_ABILITY*				0.0064	0.0183	0.0286
				(0.06)	(0.39)	(0.25)
CEO_ABILITY				0.0665	0.0392	0.1244**
				(1.15)	(1.64)	(2.06)
N	15156	15156	15156	22251	22251	22251
adj. R-sq	0.0259	0.0457	0.0466	0.0331	0.0561	0.0484

Table 5
Differential Impact of Director Social Networks on Crash Risk: Monitoring by External Auditors

This table estimates the pooled cross-sectional relation between director social networks, monitoring by external auditors, and future stock price crash risk. We measure the monitoring by external auditors based on the following two dimensions: TENURE and SPEC. The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. To economize on space, all the control variables (see Table 2) are suppressed. We report t-statistics in parentheses, based on White standard errors corrected for firm clustering. All models include year and industry fixed-effects. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.0975***	-0.0507***	-0.1159***	-0.0751***	-0.0402***	-0.0796***
	(-3.76)	(-4.84)	(-4.22)	(-3.53)	(-4.62)	(-3.55)
BOARD_CEO_TIE	-0.0994**	-0.0337*	-0.0530	-0.0682*	-0.0268*	-0.0853**
	(-2.11)	(-1.74)	(-1.08)	(-1.79)	(-1.72)	(-2.09)
*CONNECTEDNESS*TENURE*	0.0038**	0.0020**	0.0057***			
	(1.99)	(2.46)	(2.83)			
*BOARD_CEO_TIE*TENURE*	0.0043	0.0009	-0.0024			
	(1.42)	(0.73)	(-0.82)			
TENURE	-0.0040**	-0.0015**	-0.0022			
	(-2.25)	(-2.10)	(-1.28)			
*CONNECTEDNESS*SPEC*				0.0590*	0.0315**	0.0721**
				(1.70)	(2.17)	(2.00)
*BOARD_CEO_TIE*SPEC*				0.0511	0.0113	0.0132
				(0.91)	(0.49)	(0.23)
SPEC				-0.0167	-0.0023	0.0021
				(-0.54)	(-0.18)	(0.07)
N	28531	28531	28531	28531	28531	28531
adj. R-sq	0.0272	0.0480	0.0447	0.0271	0.0480	0.0446

Table 6
Differential Impact of Director Social Networks on Crash Risk: Protection of Shareholder Rights

This table estimates the pooled cross-sectional relation between director social networks, protection of shareholder rights, and future stock price crash risk. We measure the protection of shareholder rights based on the following two dimensions: LO_G (that is, an indicator equal to one if the index of Gompers et al (2003) is below the sample median, and zero otherwise) and NOUDL (i.e., an indicator equal to one for the period before the state-level adoption of universal demand law, and zero otherwise). The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. To economize on space, all the control variables (see Table 2) are suppressed. We report *t*-statistics in parentheses, based on White standard errors corrected for firm clustering. All models include year and industry fixed-effects. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.1952***	-0.0898***	-0.1522***	-0.0785***	-0.0389***	-0.0847***
	(-3.20)	(-3.62)	(-2.59)	(-3.63)	(-4.28)	(-3.79)
BOARD_CEO_TIE	-0.0509	-0.0351	-0.0758	-0.0448	-0.0214	-0.0735*
	(-0.54)	(-0.87)	(-0.82)	(-1.15)	(-1.34)	(-1.90)
*CONNECTEDNESS*LO_G*	-0.1918**	-0.0973***	-0.2041***			
	(-2.42)	(-2.92)	(-2.66)			
*BOARD_CEO_TIE*LO_G*	-0.0045	-0.0193	-0.0557			
	(-0.04)	(-0.39)	(-0.48)			
LO_G	0.0490	0.0241	0.0761			
	(0.69)	(0.82)	(1.12)			
*CONNECTEDNESS*NOUDL*				-0.0602*	-0.0249*	-0.0756**
				(-1.68)	(-1.70)	(-2.05)
*BOARD_CEO_TIE*NOUDL*				-0.0109	-0.0038	0.0078
				(-0.19)	(-0.16)	(0.13)
NOUDL				0.0468*	0.0171	0.0448
				(1.65)	(1.46)	(1.56)
N	6314	6314	6314	28366	28366	28366
adj. R-sq	0.0240	0.0550	0.0484	0.0273	0.0482	0.0447

Table 7
Impact of Director Social Networks on Crash Risk: Director-type Analysis

This table estimates the pooled cross-sectional relation between director social networks and future stock price crash risk. We decompose our measure of director external social networks based on the following four distinct classifications for monitoring-type versus non-monitoring-type directors: 1) independent directors (*IndepD*) versus non-independent directors (*NonIndepD*); 2) audit-committee directors (*AuditComD*) versus non-audit-committee directors (*NonAuditComD*); 3) short-tenured directors (*ShortTenD*) versus long-tenured directors (*LongTenD*); and 4) high-reputation directors (*HighRepD*) versus low-reputation directors (*LowRepD*). The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. To economize on space, all the control variables (see Table 2) are suppressed. We report *t*-statistics in parentheses, based on White standard errors corrected for firm clustering. All models include year and industry fixed-effects. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS												
_IndepD	-0.0314**	-0.0178***	-0.0387**									
	(-2.25)	(-3.04)	(-2.57)									
_NonIndepD	-0.0143	-0.0090**	-0.0229**									
	(-1.44)	(-2.26)	(-2.31)									
_AuditComD				-0.0276**	-0.0149***	-0.0346**						
				(-2.03)	(-2.72)	(-2.52)						
_NonAuditComD				-0.0140	-0.0080*	-0.0090						
				(-1.39)	(-1.91)	(-0.84)						
_ShortTenD							-0.0358**	-0.0200***	-0.0451***			
							(-2.44)	(-3.34)	(-3.01)			
_LongTenD							-0.0165	-0.0086*	-0.0207*			
							(-1.51)	(-1.87)	(-1.76)			
_HighRepD										-0.0372**	-0.0167**	-0.0245*
										(-2.95)	(-3.28)	(-1.85)
_LowRepD										-0.0307	-0.0175*	-0.0207
										(-1.47)	(-2.05)	(-0.99)
BOARD_CEO_TIE	-0.0502*	-0.0238*	-0.0799**	-0.0450	-0.0215*	-0.0750**	-0.0344	-0.0179	-0.0708**	-0.0059	-0.0070	-0.0637*
	(-1.66)	(-1.90)	(-2.54)	(-1.47)	(-1.70)	(-2.36)	(-1.06)	(-1.35)	(-2.17)	(-0.16)	(-0.49)	(-1.80)
N	28494	28494	28494	27595	27595	27595	21502	21502	21502	25605	25605	25605
adj. R-sq	0.0270	0.0479	0.0448	0.0254	0.0462	0.0437	0.0238	0.0426	0.0398	0.0244	0.0438	0.0415

Table 8
Director Networks and Bad News Hoarding

This table estimates the pooled cross-sectional relation between director social networks and a series of bad news hoarding channels/signals, including opaque financial reporting (*OPAQUE*), positive and negative discretionary accruals (*POS_DA* and *NEG_DA*), meeting and beating analyst forecasts using discretionary accruals (*MBEAT*), real earnings management (*ABN_PROD*, *ABN_DISEXP*, and *ABN_CFO*), tax avoidance (*CASH_ETR*), and short interest ratio (*SIR*). The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. To economize on space, all the control variables (see Table 2) are suppressed. We report *t*-statistics in parentheses, based on White standard errors corrected for firm clustering. All models include year and industry fixed-effects. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	OPAQUE	*POS_DA*	*NEG_DA*	*MBEAT*	*ABN_PROD*	*ABN_DISEXP*	*ABN_CFO*	*CASH_ETR*	*SIR*
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.0045*	-0.0039***	-0.0013*	-0.0744**	-0.0115***	0.0095***	0.0010	-0.0018	-0.0032***
	(-1.75)	(-5.55)	(-1.80)	(-2.15)	(-3.79)	(2.58)	(0.64)	(-0.50)	(-3.18)
BOARD_CEO_TIE	-0.0030	-0.0010	0.0001	0.1509**	0.0037	0.0063	0.0012	-0.0020	0.0012
	(-0.81)	(-0.96)	(0.12)	(2.74)	(0.81)	(1.08)	(0.52)	(-0.38)	(0.75)
N	28531	28788	28788	24145	28531	28531	28531	21691	28531
adj. R-sq	0.2023	0.1330	0.1036	0.034	0.5914	0.5992	0.6018	0.0801	0.2418

Table 9
Differential Impact of Director Social Networks on Crash Risk: Informed Trading

This table estimates the pooled cross-sectional regression on how the relation between director social networks and future stock price crash risk varies with informed trading. We measure informed trading by the following variables: short interest ratio (*SIR*); the ratio of total monthly put and call trading volume to stock trading volume (*OPTION/STOCK VOL*); the probability of informed trade (*PIN*); and insider trades (*INS_TRADE*). The sample covers firm-year observations with non-missing values for all variables for the period 2000 to 2015. To economize on space, all the control variables (see Table 2) are suppressed. We report *t*-statistics in parentheses, based on White standard errors corrected for firm clustering. All models include year and industry fixed-effects. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
CONNECTEDNESS	-0.0446**	-0.0209**	-0.0405*	-0.0646**	-0.0306**	-0.0494	-0.0689*	-0.0435***	-0.1243***	-0.0394*	-0.0240**	-0.0380
	(-2.13)	(-2.37)	(-1.78)	(-2.13)	(-2.42)	(-1.60)	(-1.74)	(-2.70)	(-3.03)	(-1.68)	(-2.48)	(-1.54)
BOARD_CEO_TIE	-0.0016	-0.0093	-0.0815**	-0.0727	-0.0383**	-0.1007**	-0.1680***	-0.0497*	-0.0933	-0.0439	-0.0232	-0.0748*
	(-0.04)	(-0.62)	(-2.06)	(-1.51)	(-1.97)	(-2.17)	(-2.63)	(-1.86)	(-1.36)	(-1.10)	(-1.43)	(-1.87)
*CONNECTEDNESS*SIR*	-0.2245	-0.2203	-0.4948									
	(-0.66)	(-1.62)	(-1.49)									
*BOARD_CEO_TIE*SIR*	-1.0092*	-0.2848	0.0596									
	(-1.76)	(-1.26)	(0.12)									
SIR	0.7861***	0.1992*	0.1957									
	(2.75)	(1.73)	(0.71)									
CONNECTEDNESS OPTION/STOCK VOL*				-5.6711	-4.4405	-3.0147						
				(-0.20)	(-0.38)	(-0.12)						
BOARD_CEO_TIE OPTION/ STOCK VOL*				28.0493	15.1381	3.9055						
				(0.65)	(0.90)	(0.10)						
OPTION/STOCK VOL				14.7547	-0.8266	17.8263						
				(0.53)	(-0.08)	(0.72)						
*CONNECTEDNESS*PIN*							0.0336	0.0525	0.2876			
							(0.19)	(0.74)	(1.58)			
*BOARD_CEO_TIE*PIN*							0.4319	0.0705	0.0004			
							(1.35)	(0.51)	(0.00)			

PIN							-0.2964	0.0343	0.0324			
							(-1.61)	(0.44)	(0.14)			
*CONNECTEDNESS*INS_TRADE*										0.0016	0.0005	-0.0094
										(0.15)	(0.11)	(-0.76)
*BOARD_CEO_TIE*INS_TRADE*										0.0044	0.0066	0.0227
										(0.21)	(0.77)	(1.01)
INS_TRADE										0.0307**	0.0136***	0.0239**
										(3.16)	(3.52)	(2.30)
N	28531	28531	28531	19173	19173	19173	20744	20744	20744	20041	20041	20041
adj. R-sq	0.0271	0.0479	0.0445	0.0191	0.0395	0.0400	0.0346	0.0591	0.0519	0.0216	0.0400	0.0398

Table 10

Tests on the Endogeneity of Director Network Size

This table reports the results of endogeneity tests on director network size. Panel A reports the results of the difference-in-difference estimation within the subsample of firms whose directors retire during the sample period. *POSTRETIRE* is set to 1 (0) for the year immediately after (before) the director retirement. *LARGE_DECREASE* is set to 1 if the absolute value of the decrease in the board network size is above the sample median value, and 0 otherwise. Panel B reports the results on the determinants of changes in director networks within the subsample of firms with requisite data. Δ*CONNECTEDNESS* is the change in *CONNECTEDNESS* from year t-1 to t. To economize on space, all the control variables (see Table 2) are suppressed in Panels A and B. We report t-statistics in parentheses, based on White standard errors corrected for firm clustering. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively. All other variables are defined in Appendix A.

Panel A– Stock price crash risk and director network changes due to retirement

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Dep. Var.=	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$	$NCSKEW_{T+1}$	$DUVOL_{T+1}$	$COUNT_{T+1}$
LARGE_DECREASE	-0.1183	-0.1167	-0.2469			
	(-0.56)	(-1.21)	(-0.79)			
POSTRETIRE	-0.2906	-0.1412	-0.3432	-2.7241**	-1.3487***	-3.5925**
	(-1.29)	(-1.49)	(-1.42)	(-2.41)	(-2.91)	(-2.59)
*POSTRETIRE*LARGE_DECREASE*	0.6606**	0.3482***	0.7927**	0.5250	0.2668**	0.7134*
	(2.17)	(2.68)	(2.08)	(1.59)	(1.97)	(1.76)
BOARD_CEO_TIE	-0.0800	0.0156	0.2158	1.3740**	0.6762**	1.4233*
	(-0.34)	(0.15)	(0.76)	(2.04)	(2.44)	(1.72)
Year fixed effect	YES	YES	YES	YES	YES	YES
Industry fixed effect	YES	YES	YES	NO	NO	NO
Firm fixed effect	NO	NO	NO	YES	YES	YES
N	422	422	422	422	422	422
Adjusted R^2/Within R^2	0.240	0.278	0.228	0.195	0.124	0.227

Panel B – Determinants of changes in director networks

Dep. Var.=	**Model 1** ΔCONNECTEDNESS	**Model 2** ΔCONNECTEDNESS	**Model 3** ΔCONNECTEDNESS
LAG_NCSKEW	-0.0008		
	(-0.70)		
LAG_DUVOL		0.0011	
		(0.44)	
LAG_COUNT			0.0010
			(1.08)
LAG_BOARD_CEO_TIE	-0.0122***	-0.0121***	-0.0121***
	(-3.00)	(-2.99)	(-2.98)
LAG_DIV	0.0078**	0.0076**	0.0076**
	(2.14)	(2.09)	(2.08)
LAG_KUR	0.0004**	0.0003**	0.0003**
	(2.46)	(2.19)	(2.26)
LAG_SIGMA	0.2493	0.2144	0.2217
	(0.54)	(0.46)	(0.48)
LAG_RET	14.5025	13.3130	13.3175
	(1.41)	(1.30)	(1.30)
LAG_MB	0.0004	0.0004	0.0005
	(0.74)	(0.80)	(0.83)
LAG_LEV	-0.0390***	-0.0390***	-0.0390***
	(-4.41)	(-4.41)	(-4.40)
LAG_LNSIZE	-0.0051***	-0.0050**	-0.0050**
	(-2.63)	(-2.57)	(-2.55)
LAG_ROA	-0.0060	-0.0062	-0.0064
	(-0.35)	(-0.37)	(-0.38)
LAG_OPAQUE	0.0354**	0.0354**	0.0354**
	(2.50)	(2.51)	(2.50)
LAG_SIR	-0.0083	-0.0086	-0.0095
	(-0.28)	(-0.29)	(-0.32)
LAG_SPEC	-0.0024	-0.0024	-0.0024
	(-0.79)	(-0.78)	(-0.79)
LAG_ABN_PROD	0.0201	0.0202*	0.0202*
	(1.64)	(1.65)	(1.65)
LAG_ABN_DISEXP	-0.0010	-0.0008	-0.0007

	(-0.11)	(-0.09)	(-0.08)
LAG_ABN_CFO	0.0103	0.0105	0.0107
	(0.56)	(0.57)	(0.58)
LAG_DTURN	0.0139	0.0139	0.0138
	(0.77)	(0.77)	(0.76)
LAG_AGE	0.0004**	0.0004**	0.0004**
	(2.07)	(2.07)	(2.07)
LAG_TENURE	0.0002	0.0002	0.0002
	(0.86)	(0.86)	(0.85)
LAG_BIGN	-0.0131**	-0.0131**	-0.0131**
	(-2.31)	(-2.33)	(-2.33)
LAG_ANA	0.0247***	0.0244***	0.0243***
	(7.90)	(7.80)	(7.79)
LAG_INST	-0.0084	-0.0084	-0.0084
	(-1.39)	(-1.39)	(-1.39)
LAG_DISTANCE	0.0020	0.0021	0.0021
	(0.69)	(0.70)	(0.72)
_CONS	0.0949**	0.0940**	0.0934**
	(2.10)	(2.09)	(2.07)
Year fixed effect	YES	YES	YES
Industry fixed effect	YES	YES	YES
Adjusted R^2	0.007	0.007	0.007
N	20421	20421	20421